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The Credit Rating Puzzle

A study on the relationship between equity returns and corporate credit ratings in the US stock market

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Abstract

This study search to investigate the relationship between credit risk, measured by S&P long-term domestic issuer credit rating, and stock returns. Analyzing 3,172 companies over the period January 1985 to December 2013 we investigate if it exist a relationship using several methods. In the first part we generate portfolios sorted by credit rating, and analyze how certain firm characteristics and returns varies between good and bad rated stocks. Secondly, we are running panel data regressions on individual securities controlling for several control variables, such as book-to-market, market value of equity, and share turnover. We find a negative relationship between stock returns and credit ratings, suggesting that worst rated stocks on average yield lower returns than better-rated stocks. Market value of equity decrease monotonously as rating deteriorates. However, we also find that the credit rating effect is related to worst rated stocks. Excluding the worse rated stocks, we find no statistical evidence that there exist a negative effect, until we include BB- rated stocks. In times of recession the effect is stronger than in expansions, suggesting that credit ratings may be of more interest for investors when there exist a higher risk of financial distress. Around downgrades (upgrades) returns have a downward (upward) trend ex-ante the event. After change in credit quality, we notice returns bounce back on a level equal securities that did not experience any rating action. It is no clear explanation to this negative relationship. Existing literature suggest that majority shareholders can extract private benefits from distressed companies, buying the companies assets or output at lower price. Hence, the observed return is lower than the realized return. For smaller companies with low analyst coverage, bad news travel more slowly than in large firms with higher analyst coverage, and the underperformance can be explained due to investor's underreaction to negative information.

Preface

This master thesis symbolizes the final stages of my Master of Science in Economics and Business Administration. I have enjoyed working with the thesis, and I have been challenged in both financial theories and econometrics models. Finance is an area within economics I always have been interested in, and it was natural to dig deeper into this specific area.

When thinking about a topic of interest I emphasized that it should be innovative, of interest to the academic environment, and something that strikes my interests. During the search of an interesting topic I got introduced to look into the relationship between credit rating and stock returns. I found the topic interesting because credit risk and credit ratings have received an increased focus in recent years, especially in light of the financial crisis. In addition, it is a little explored area, and I hope the findings will be of interest to financial institutions and academia.

Throughout the whole process I have learned a lot about empirical work, which is way more complex than a fabricated case study. One thing that surprised me was the difficulty of getting a reliable and "good" data sample. Even though the data was easily available, it took a lot of effort to clean and organize the data to make it appropriate for analysis.

I would like to thank my supervisor, Torfinn Harding, who has been very helpful during the process of writing the thesis. I also wish to express my gratitude to Jonas Osland in Skagenfondene for great feedback around the practical aspects related to the problem.

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Alexander Hopland

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1. Introduction

Imagine that we could split the stock market in two, Investment grade (IG) and not investment grade (NIG) securities. Imagine further that we extend the mindset from the bond market, where high rated bonds have low yield and riskier bonds have high yield and applies it to the stock market. This description is an extreme viewpoint when we relate it to the stock market, because there are so many other factors than the risk of default that determines the value of a company. An article in The economist (Buttonwood, 2014) problematize that it is strange to split the universe into two (IG and NIG) when you are on the equity side. But is it possible to observe the same pattern? In a way, this thesis is looking at the stock market from this perspective.

Today's technology allows information spread quickly, and to many. Investors are facing an ocean of information, and are using considerable amounts of resources to collect, filter and utilize relevant information to beat the market and generate returns. Challenges related to risk management is highly relevant in light of the financial crisis that hit the world economy not many years ago. Prior to the crisis we observed an increase in irresponsible mortgage lending. Financial companies packaged the so-called subprime loans into pools, and the risk seemed low. The structured products received a high rating from the credit rating agencies (CRAs), and investors bought instruments in good faith belief that the instruments had a low risk-exposure and high returns relatively for its risk. The investors trusted the CRAs, but they got it wrong this time. The bottom line is that there exist information asymmetries in the credit market. To assess the credit risk of a company that has, for instance, business in several countries, operates in many industries, facing various political reforms, and has a great exposure to changes in commodity prices etc. is difficult. CRAs exist precisely to fill this gap and reduce the information asymmetry between the participants in the marketplace. The goal is to provide an objective opinion about securities' creditworthiness and credit quality.

Several studies investigate the relationship between leverage and returns. Optimal leverage and capital structure varies between industries. Corporate credit rating, however, is an objective assessment of an entities ability to pay its obligations, and may be a better measure to identify a relationship between financial solvency and stock returns. In the real world returns relative to rating is being widely discussed in the bond markets, but not in the equity markets.

The question we ask ourselves is whether we can use this information as an input in investment decisions. Is there a relationship between corporate credit ratings and stock returns? We examine if the corporate credit ratings provided by the CRA have any impact on a security's return, and if there are any differences between rating categories. We are interested in the effect of credit rating as a signal, not as a reflection of fundamentals everyone can observe. In addition, to test the relationship between credit ratings and performance, we investigate whether there are certain characteristics that characterize the best and the worst rated securities. 3,172 distinct securities are analyzed using panel data regression, testing whether creditworthiness, measured by credit rating, is a factor that has an impact on stock returns. Especially, we will expand the analysis to analyze the effect in depth during expansions and recessions. Another side of the case is how the market reacts to changes in rating. Analyzing how returns behave around upgrades and downgrades are interesting to understand how the market interprets new information from the CRAs.

Our main research question is formulated as follow:

"Is there a relationship between stock returns and corporate credit ratings?"

Initially, we anticipated that investors are compensated for bearing risk. A worse credit rating implies that the company has a higher probability of default hence more exposed to credit risk, and other types of risks. The risk-return tradeoff suggests that an increase in risk should yield higher expected returns. However, existing literature find a negative relationship between distressed firms and stock returns (Griffin and Lemmon, 2002, Campbell et al., 2008, Avramov et al., 2009). We contribute to the existing literature by focusing on differences during recessions and expansions, and between sectors. We also try to argue for why we might observe a negative relation. In times of recessions, the risky firms might have a lower success rate, which may lead to lower returns and more frequent bankruptcies. It is interesting to investigate whether an eventually relationship persists or changes. Differences between sectors, both in business risk and firm characteristics, may cause that there are differences among sectors. Lastly, we also confirm the negative relationship using a longer time horizon than earlier, which includes an additional recession.

The empirical strategy is to mainly apply panel data regressions on individual securities. We show the results using different methods, using the Fama-MacBeth procedure as our main procedure. We control for size, book-to-market, and share turnover in our model. Initially we form ten portfolios from the best to worst rated companies to get an overview of mean and median return and other firm characteristics.

Along the way there are also some pitfalls to consider. First of all it is difficult to isolate the effect of credit rating and equity returns. It exists a lot of noise in the equity market and returns are not only driven by fundamental factors, but also a lot of speculations, anomalies, expectation, and mood among the participants. To account for this we will control for several factors that previously are shown to explain equity returns. Second, we cannot for sure know that return follows rating or reverse. This is in econometric literature referred to as reverse-causality. To control for this we introduce lagged rating variables in the regressions. Third, sample selection bias and econometrical challenges, like heteroskedasticity and multicollinearity. Fourth, the announcements of rating outlooks and CreditWatch's may interfere with the results. Standard and Poor's may issue an updated rating outlook if they anticipates a credit rating to change in the coming 6 to 24 months (90 days for CreditWatch). However they can upgrade or downgrade the corporate immediately, if all the available information suggests a change in rating. It is possible, that the market already has priced this new information before rating changes, and if the anticipated credit rating occurs there may not be any significant adjustment in the stock price.

The rest of the thesis is organized as follow; in chapter 2 we will analyze existing literature and provide some background information. Further, chapter 3 will explain the data sample and provide descriptive statistics. Chapter 4 explains the methods used to test the research question. In chapter 5 the results from the quantitative analyze is shown, before we conclude in the last section.

2. Theoretical framework

The theoretical foundation of this thesis is essentially divided into three main sections. First, it is important to gain insight of what credit risk is, and why it is an important criteria in economic decisions. Second, as a natural transition from the first part, we will provide a brief overview of what a CRA is and how they contribute to the equity markets. Further we will give an explanation of the different rating measures and what they represents. Third, we will provide a presentation about the financial theories and empirical work related to factors that contribute to explain stock returns.

2.1 Credit risk

Companies are exposed to various types of risk. Duffie and Singleton (2003, p. 3) categorizes them into the following categories:

- Market risk – the risk of unexpected changes in price or rates
- Credit risk – the risk of changes in value associated with unexpected changes in credit quality
- Liquidity risk – the risk that the cost of adjusting financial positions will increase substantially or that a firm will lose access to financing
- Operation risk – the risk of fraud, system failures, trading errors (e.g., deal mispricing), and many other internal organizational risks
- Systemic risk – the risk of breakdowns in market wide liquidity or chain reaction default

Further, Duffie and Singleton claims that market risk includes the risk of default, or fluctuation in the credit quality of one's counterparties. Hence, credit risk can be assessed to be one source of market risk. In credit markets (and capital markets) it exists market imperfection. The most noteworthy market imperfection in the credit market is information asymmetry, which seed for adverse selection and moral hazard. Market imperfections lead to additional benefits of controlling counterparty credit risk and limiting concentration of credit risk by industry, geographic region and so on (Duffie and Singleton, 2003). In the following we will explain what credit risk is, and further give an overview over important reasons to control credit risk.

2.1.1 Definition of credit risk

Credit risk can be defined as "the risk of default or of reduction in marked value caused by changes in the credit quality of issuers or counterparties" (Duffie and Singleton, 2003, p. 4). Wagner (2008, p. 69) defines credit risk "as the risk of loss resulting from failures of counterparties or borrowers to fulfill their obligations. Credit risk appears in almost all financial activities, and it is therefore important to measure, price and manage accurately."

From the definitions we can tell that credit risk is characterized by two risks, default risk and the spread risk, which is the change in the credit quality. For instance, changes in the quality due to some loss means greater risk of default and lower expected return. The relative decrease in the expected return of this company compared with a risk free security causes a decline to the demand for the security. Simultaneously with the company becoming more risky, the price fall and interest risk becomes greater. Assuming risk adverse parties, lenders are likely to charge a premium to bear an extra risk that the borrower can default (Pereira, 2013).

2.1.2 Why manage credit risk?

During the 1990s it emerged an increased interest for using credit derivatives for managing credit risk. "Credit derivatives are financial contracts that transfer the (credit) risk and return of an underlying asset from one counterparty to another without actually transferring the underlying asset" (Wagner, 2008, p. 70). The use of credit derivatives is used by a wide variety of stakeholders, from commercial banks to nonfinancial firms, who seek to buy protection from loss from customers or suppliers.

Considering a world with perfect capital markets (Modigliani and Miller, 1958) financial transactions has no impact on the market value of a firm. As we know, it exists several market imperfections in the capital markets. This leads to benefits for financial institutions, and others, for bearing and controlling financial risk, especially in the case of extreme losses. During sufficient large losses, financial distress cost become apparent in terms of financing premium for replacing capital, the liquidity cost of asset firesales, reduction of business, and loss of reputation (Duffie and Singleton, 2003).

Information assymetric

Often there exist information asymmetric between lenders and borrowers. In most cases the borrower know more about its own credit risk than the lender. Since the lender has an information disadvantage it may find it profitable to limit borrower's access to its funds (Duffie and Singleton, 2003). To the extent there is also asymmetric information between buyers and issuers of equity, because the issuers know more about the company (inside information) than the buyers.

Asymmetric information causes moral hazard and adverse selection. Adverse selection relates to the occurrence of an undesirable result when, in this case, borrowers and lenders have asymmetric information. Adverse selection makes the riskiest borrowers more likely to ask for funds than the safest one (Duffie and Singleton, 2003). Relating this to equity, more risky issuers are likely to ask for funds than the safest one.

> "Based on adverse selection, quantitative exposure limits are analogous to a stock specialist's limit on size for market orders. Setting a smaller limit reduces volume and thereby limits profits. Setting a larger limit encourages the selection of positions with adverse credit quality. An "optimal" limit is one that trades off these two effects. We expect that limits should be based on any information available on credit quality. For example, Aaa-rated counterparties should have higher limits than Baa-rated counterparties, for there is a relatively small likelihood that a large position initiated by an Aaa-rated counterparty is designed to exploit the broker-dealer's incomplete information of the counterparty's credit quality" (Duffie and Singleton, 2003, p. 27).

"Moral Hazard refers to the idea that individuals will change their behavior if they are not fully exposed to its consequences" (Berk and DeMarzo, 2011, p. 528). In credit markets, moral hazard exists when an issuer ex-post the issue starts to increase its business or financial risk. Continuously monitoring the issuers, CRAs change the ratings if warranted, and guard the investors against moral hazards from the management in the firm. What makes Credit Risk to be what it is is the lack of information. CRAs exist to reduce these imperfections, and enhance capital market efficiency and transparency (Langhor and Langhor, 2008).

2.2 Credit rating agencys and ratings

In 1859 the first rating guide was published in the US. The credit rating industry has expanded over the years due to increased complexity and borrower diversity in the financial markets. Investors rely more and more on the CRAs opinions to form a view of an entity's creditworthiness (Cantor and Packer, 1994). Today there are three major rating agencies in the US: Standard and Poor's (S&P), Moody's and Fitch. These three companies had in 2012 96% of all credit ratings (U.S. Securities and Exchange Commission, 2012). All the three CRAs have different definition of what credit ratings are and what purpose they do serve. However, the content is essentially equal, and since S&P ratings are used in this thesis we will focus on their definitions and methodology in the following.

According to SEC (2013) "A credit rating agency assesses the creditworthiness of an obligor as an entity or with respect to specific securities or money market instruments." This means that they express their opinion on whether a corporation or another unit is able to meet its financial obligations in full and on time. Credit ratings can also speak to the credit quality of an individual debt issue, and therefore, it is "a judgmental process of ranking and classifying credits into different levels of risk categories" (Ong, 2002, p. 3). Credit ratings are forward looking, by evaluating current and historical information and assess the potential impact of foreseeable future events (Standard & Poor's).

We distinguish between long-term and short-term ratings. Further there is a distinction between issue-specific credit ratings and issuer (counterparty) credit ratings. An overview over the different types of ratings is shown in Table 1.

Table 1
Different type of credit ratings

	Issue-specific credit ratings	Issuer credit ratings
Long-Term	Notes, syndicated bank loans, bonds and debentures etc.	Corporate credit ratings, Counterparty ratings, Sovereign credit ratings
Short-Term	Commercial paper, put bonds/demand bonds, Certificate of deposit programmes	Same as long term

Issuer credit rating is an opinion on the obligor's overall capacity to meet its financial obligations. It can be either long-term or short-term. Prior to 1998, the item represents the issuer senior debt rating, which is a current assessment of the creditworthiness of an obligor with respect to a senior or subordinated debt obligation (Wharton Research Data Services (WRDS)). Short-term ratings assess the credit quality with respect to short-term instruments in the relevant market.

An issue credit rating is also a forward-looking opinion about the creditworthiness of an obligor. In contrast to issuer ratings, it assess the creditworthiness with respect to a specific financial obligation, a specific class of financial, or a specific financial program.[1]

S&P can also publish outlook and Creditwatch if they anticipate a credit rating to change in the coming 6 to 24 months, or within 90 days for CreditWatch. It can be "positive", "negative", "stable" or "developing", indicating whether we can expect a upgrade, downgrade, no change, or if the direction is uncertain. An update in rating outlook or placing a rating on CreditWatch does not mean a rating change is sure to happen. Also, S&P can change the credit rating immediately if all the information available warrants a rating change (Standard & Poor's).

2.2.1 Rating scales

In this thesis we are looking at issuer credit ratings, more specifically corporate credit ratings. This is an opinion on the obligor's overall capacity to meet its financial obligations. Appendix 1 explains the different rating categories used by Standard and Poor's. Credit ratings ranges from AAA to D, where AAA is the best rating and D is the worst. Ratings from AA to CCC may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the major rating categories. Rating AAA to BBB- is considered investment grade and BB+ to D is considered speculative grade (Standard & Poor's).

How we interpret the ratings require a more thorough explanation. Langhor and Langhor (2008) emphasize that, first of all, ratings address benchmark measures of probabilities of default, not probabilities. Second, ratings want to be cycle-neutral and don't swing up and down to reflect, for instance, the last quarter's earnings report. The financial condition of the issuer is measured over years to avoid transitory anomalies. A consequence of this behavior

[1] http://www.standardandpoors.com/ratings/articles/en/us/?articleType=HTML&assetID=1245365752249

may cause us not to find any clear pattern between stock returns, because the stock market tends to follow the business cycle. Third, ratings are descriptive, not prescriptive, of a debt situation. In order to maximize shareholder value, shareholders optimizes the amount of debt. In a way, shareholders trade off the cost of a lower credit rating against the benefits of more debt. If we keep business risk constant, income taxes and the agency costs of equity favor increasing debt. On the other hand, the corresponding increases in interest cost of debt, expected costs of financial stress, and agency cost of debt have the opposite effect. This implies that there is an optimal debt-to-assets ratio, which maximize enterprise value and minimize overall cost of capital. However, "the optimal credit rating for a company's debt at a given point in time may be anywhere from speculative to the safest investment grade" (Standard & Poor's, 1998, p. 2., quoted Langhor and Langhor (2008), p.81). Fourth, ratings measure credit risk, they don't price it. Default risk is only one factor that influence security risk, among with market risk. Duffie and Singleton (2003) claim that credit risk is included in market risk. Lastly, credit ratings are credit ratings, not equity ratings. Credit ratings look more on the downside and a longer time horizon than equity analysis.

2.2.2 Rating methodology[2]

In Standard and Poor's Guide to Credit Rating Essentials, Standard and Poor's illustrate their methodology as shown in Figure 1. A typical approach is to use both primarily analysts and mathematical models. When analyzing corporations they don't solely base their opinion on mathematical models and public known information. An analyst driven approach is often used, where an analyst is assigned, often in conjunction with a team of specialists to evaluate the entity's creditworthiness. In addition to public information and reports, they interview and discusses with the issuer's management to assess the entity's financial condition, operating performance, policies and risk management strategies.

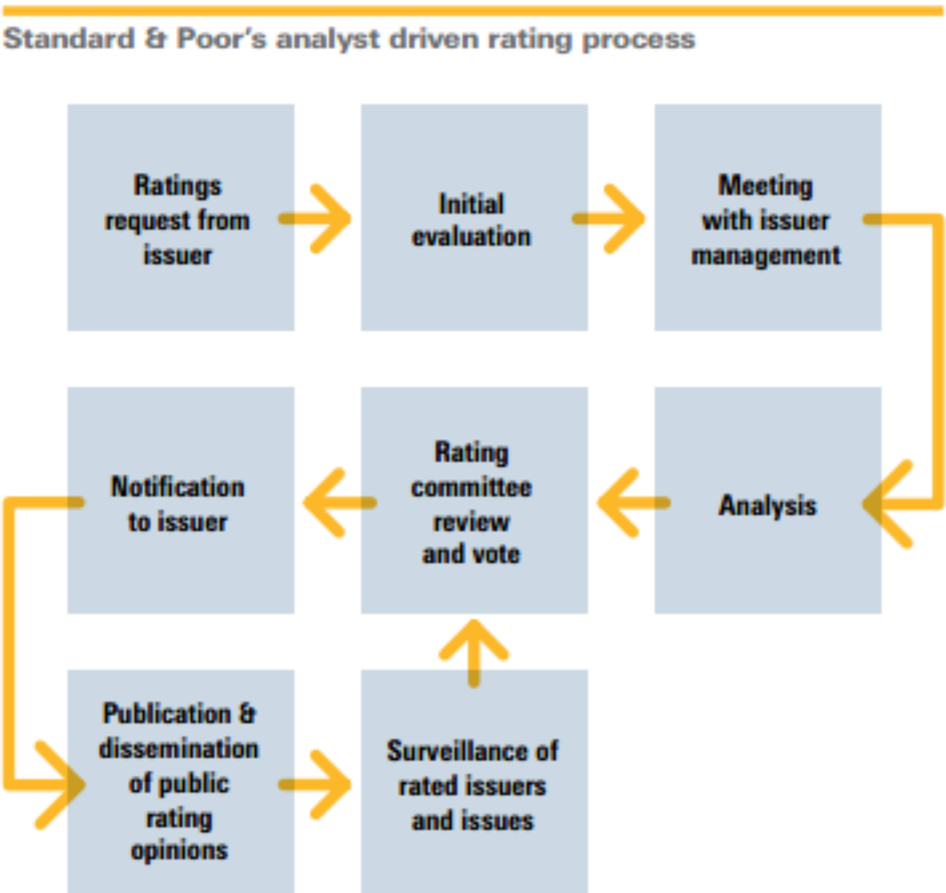
Bearing in mind that CRAs utilize non-public information, indicates that the ratings may reflect information that market participants have not yet taken into account. Assuming that the stock market is efficient, all information that is relevant for the value of the firm is already included in the stock price. This is often referred to as the efficient market hypothesis (EMH). The rationale behind this is that if you know something other doesn't know you can take

[2] The following are primarily sourced from STANDARD & POOR'S Guide to Credit Rating Essentials. What are credit ratings and how do they work?, where no other source is mentioned

advantage of that. Investors will have an incentive to spend time and resources to uncover new information. This leads us over to the efficient market paradox (Grossman and Stiglitz, 1980), which emphasize that if every investor believes the market is efficient, no one would analyze the market. If it is the case that CRAs know information that is not reflected in stock prices, credit ratings and changes in credit rating reflects information that the current stock price doesn't reflect prior to credit rating announcements. We should then expect a reaction in the market in case of a change in credit quality.

Credit ratings can be assigned to both issuers and issues. This master thesis focuses on issuers (corporations), and we will therefore focus on that methodology.

Figure 1
Standard & Poor's analyst driven rating process.



Source: http://img.en25.com/Web/StandardandPoors/SP_CreditRatingsGuide.pdf

Standard and Poor's evaluates the issuer's ability and willingness to repay its obligations in accordance with the terms of these obligations to assess the creditworthiness of an issuer. What kind of risk factors that are analyzed depends on the type of the entity. For a corporate issuer, many financial and non-financial factors are considered, including key performance indicators, economic, regulatory and geopolitical influences, management and corporate governance attributes, and competitive position. Business risk includes country risk, industry characteristics, company position, product portfolio/marketing, technology, cost efficiency, strategic and operational management competence, profitability/peer group comparisons (Langhor and Langhor, 2008). Financial indicators include accounting, governance, risk tolerance, financial policy, cash flow adequacy, capital structure and liquidity/short term factors. The development of business cycles, industry-specific factors and other macroeconomic factors are considered for high-grade credit ratings.

2.2.3 Why do credit ratings matter?

The information asymmetries presented in 2.1.2 are one of the reasons for why CRAs exists. They exist to shorten the distance between lenders and borrowers. Credit ratings can be useful for several interest groups. Survey results find that credit ratings are CFOs second highest priority when determining their capital structure (Graham and Harvey, 2001). Ratings can in addition to work as proxies for default risk, generate discrete costs and benefits to firms. When CFOs are choosing and planning their financing choices, ratings and possible rating changes are integrated in their analysis (Langhor and Langhor, 2008).

Issuer credit rating provides a measure of credit risk. Obtaining a rating is a costly affair, so why would issuers like to be rated? The first reason is to get access to the public bond market, and thereby more funding alternatives, and accessing a broader investor base. Further, it will provide a higher flexibility in terms of market timing and terms/covenants. Second, credit ratings can help the company to compete. Issuers would like to have a higher rating in order to pay a lower yield at issue, because credit ratings and credit spreads tends to be negatively correlated (Langhor and Langhor, 2008). Enhanced transparency, name recognition and credit standing in international capital markets can make it easier to obtain financing. Lastly, the issuer can get improved bargaining power with banks, suppliers etc. Better deals can result in higher margins and improved earnings, which can lead to a higher value and stock price.

For investors credit ratings helps to compare different investment opportunities and to assess credit risk and manage their investment portfolios. It further makes investors better to understand better the risk and uncertainties they face while investing (Langhor and Langhor, 2008). Investment bankers may use credit ratings to benchmark relative credit risk and use credit ratings as a supplement to their own analysis. Credit ratings measure the credit risk of the issuers business objectively (Langhor and Langhor, 2008). Although credit ratings are forward looking, S&P emphasizes that ratings are not buy, sell or hold recommendations or a measure of asset value, and should not be used as the only criteria in an investment decision.

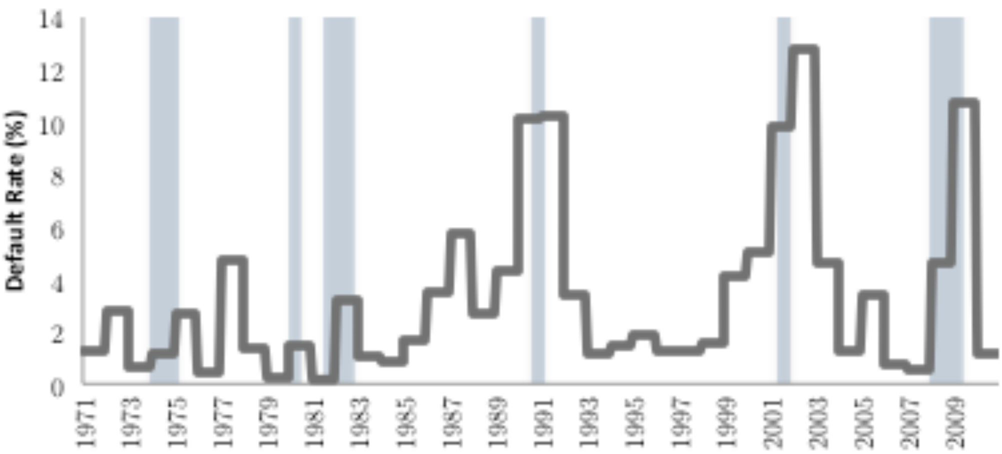
2.2.4 Drivers of corporate defaults

There are many different factors that make companies go bankrupt. Yet it is not so that they apply to all companies, as there are companies that do well in bad times and companies that do poorly in good times. Langhor and Langhor (2008) groups them into three main groups:

- Macroeconomic activity and overall default rates
- Economic sectors and variations in default rates
- Company specifics

During recessions default rates tend to increase, and during expansions default rates tend to decrease. Hence, credit risk is cyclical. Figure 2 show historical default rates in the period 1971 to 2010. The shaded areas are recessions as defined in NBER. We can see a consistent pattern where default rates increases prior and during recessions.

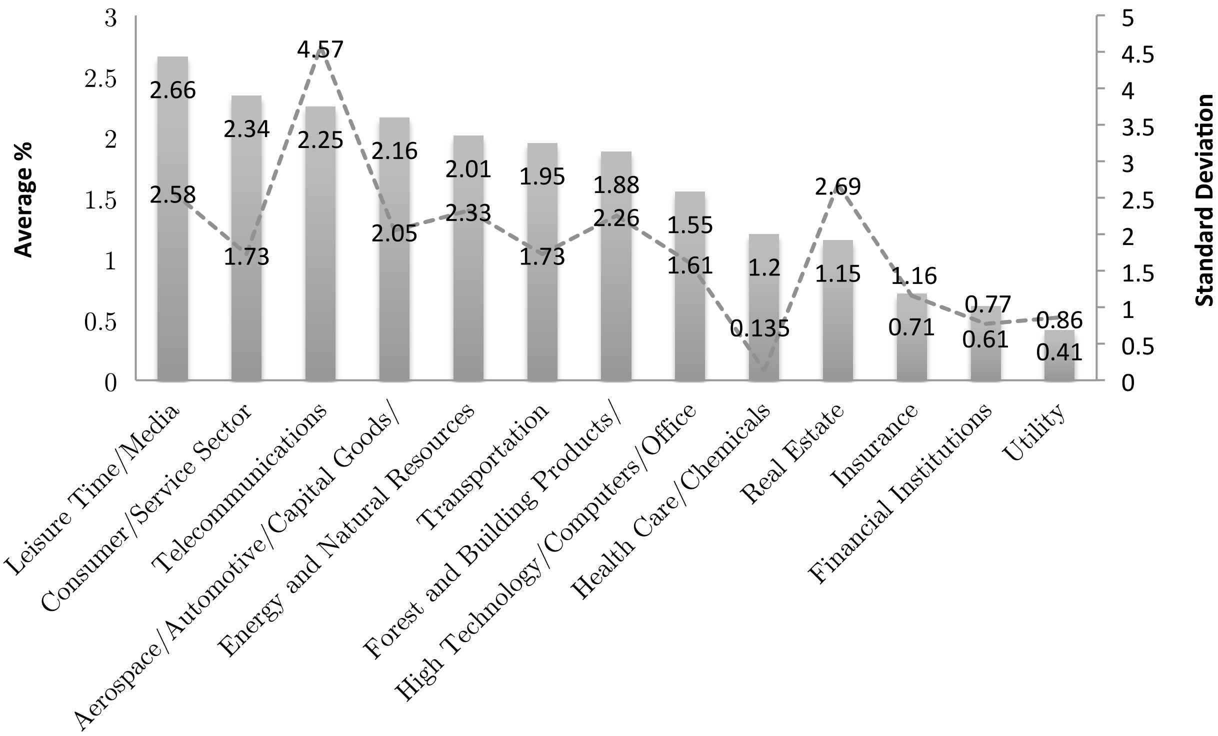
Figure 2
Default Rate and Recessions (1971-2009)



Source: Altman and Kuehne (2011), and NBER

Default rates vary across industrial sectors. Figure 3 shows that Leisure time, media, consumer/service sector, telecommunication, Aerospace/Automotive/Capital Goods/metal, and Energy and natural resources, are sectors that have the highest default rates. In contrast, Utility, financial institutions, insurance and health care have the lowest default rates. Not surprisingly, we see that the sectors with high default risk tend to be more sensitive to the business cycle than sectors with low default risk, with exceptions. One explanation can be that when times get worse, reduction of consumption is one of the first mechanisms that occur. Furthermore, sectors that have a high standard deviation, which makes it difficult to predict defaults also have the highest default rates.

Figure 3
Default rates by industry: Average and Standard Deviation (1981-2006)



Source: Vazza et al. (2007), as cited in Langhor and Langhor (2008)

2.3 Risk and return in equites

Moving over from credit risk and CRAs we will now briefly discuss risk and return in equities. In finance we often say that the value of an asset is the net present value of the assets future cash flows, discounted by a reasonable discount rate. If the asset is equity, we often analyze historical performance, competitor's performance and how we think the company will perform in the future and how the market and economy in general will develop. In other words we investigate a broad set of indicators from statements, from the management group, to what the interest rate is going to be in the next ten years.

The relationship between risk and return is an extensively used concept in finance. Investors demand a risk premium to invest in riskier assets, and empirically over time riskier assets yield a higher return, but fluctuates more. When we are talking about stocks we refer to fluctuations as volatility. Usually stock returns fluctuates due to two types of risks (Berk and DeMarzo, 2011):

- Firm-specific news (Idiosyncratic risk), which is good or bad news about a specific company
- Market-wide news (Systematic risk), which is news about the economy as a whole and affects all firms

The Capital Asset Pricing Model (CAPM) is a widely used method to calculate the cost of equity.

$$r_e = rf + \beta \times (r_m - r_f)$$

β is a measure of the equity's sensitivity to the market, and is an expression for the systematic risk. The CAPM suggests that the cost of equity is the risk-free rate plus the excess return on the market multiplied with β. As β increase, investors demand a higher expected return.

2.3.1 Stock returns and explanatory factors – Litterature review

In traditional financial theory it is a fundamental principle that higher-risk assets should require higher expected returns. Early studies by Sharpe (1964) and Lintner (1965), among others, demonstrates that a stock's expected return is influenced by a systematic risk measured by β. Later, several studies have tested the model and investigated the relationship between stock returns and other variables that contribute to explain stock returns.

Fama and MacBeth (1973) test the relationship between average return and risk for NYSE. They use a "two-parameter" portfolio model. Their conclusion is that they cannot reject the hypothesis that average return reflects to risk-averse investors to hold efficient portfolios. On average there is a positive tradeoff between risk and return.

Early work by Basu (1977) tests the performance of common stocks against their price-earnings ratio (P/E). He finds that P/E ratio may be indicators of future investments performance due to exaggerated investors expectations. Further Banz (1981) examines the relationship between the return and market value of NYSE common stocks. He finds a "size effect", where smaller firms have had a higher risk adjusted returns than larger firms on average. He emphasize that the effect occurs between large and very small firms. The effect is not so strong among the largest and "average size" firms. Moreover, he concludes that there is no theoretical foundation for such an effect, and underscore that size can be a proxy for one or more true but unknown factors correlated with size.

One of the cornerstones in asset pricing literature, Fama and French (1993), introduced a three-factor model to describes stock returns based on their previous paper Fama and French (1992). The three factors are high minus low (HML), small minus big (SMB), and excess return on the market (MRKTRF). HML measures respectively excess returns of small companies over big companies, and SML excess returns of value stocks over growth stocks. They conclude that these three factors explain the cross-section of average stock return. Firms with a high (low) book-to-market tend to have low (high) earnings on assets. They also find that small firms tend to have lower earning on assets than big firms. Later in our analysis we will apply this model on the credit rating portfolios, to investigate the magnitude each portfolio load on the three factors MRKTRF, HML, and SMB. We will also include the momentum factor as in (Carhart, 1997), which actually makes it a four factor model.

Brennan et al. (1998) are moving from testing non-risk factors to risk factors. In addition to confirming Fama and French, they find a negative relationship between average returns and trading volume. They argue that the negative relationship is consistent with a liquidity premium in asset prices. Their methods differ from some of the previous papers mentioned, where portfolio are constructed and sorted on some sort of criteria. Following Roll (1977) who points out that the use of portfolios is problematic, Brennan et al. are running the analysis on individual securities.

There are a lot of papers testing and confirming the main findings above. Surprisingly, there are quite few that are studying how credit rating or distress risk is related to stock prices. A paper by Griffin and Lemmon (2002) examines the relationship between book-to-market equity, distress risk, and stock returns. They find that among firms with highest distress risk as proxied by Ohlsons's O-score (Ohlson, 1980), the difference in returns between high and low book-to-market securities is more than twice as large as that in other firms. They also find a negative cross-sectional correlation between credit risk and future stock returns. The results are driven by extremely low returns on firms with low BTM. An explanation to this could be that high distress risk leads to a greater chance to be mispriced by investors.

Campbell et al. (2008) also find that stocks with a high risk of failure tends to deliver anomalously low average returns. They find that the distressed portfolios have high standard deviation, market betas and loadings on Fama and French (1993) small-cap and value risk factors. They try to explain this anomalous underperformance due to investors underraction to negative information about company prospects. Corporate managers have incentives to withold bad news, and the bad news reach the market gradually. For larger companies with a greater equity analyst coverage, equity analysts can speed up the flow of information (Hong et al., 2000). Kalckreuth (2005) have argued that investors can extract private benefits of distressed companies, especially those who are unlikely to survive. These benefits is for instance, buying the company's output or assets at lower prices. Hence the return for the majority sharholders may be higher than the return we measure to outside shareholders.

A similar approach as our study is conducted by Avramov et al. (2009), which find that low credit risk firms realize higher returns than high credit risk firms. Investors seem to pay a premium for bearing credit risk. However, they conclude that the credit risk effect exists due to the poor performance of low-rated stocks during periods of financial distress. "*Around rating downgrades, low-rated firms experience considerable negative returns amid strong institutional selling, whereas returns do not differ across credit risk groups in stable or improving credit conditions. The evidence for the credit risk effect points towards mispricing generated by retail investors and sustained by illiquidity and short sell constraints.*"

This study, in addition to confirming previous studies, extends the existing literature in several ways. We have more focus on the credit rating effect during business cycles. Further we investigate whether there are any differences among industries motivated by Langhor and Langhor (2008) showing differences in default rates between industries.

3. Data and variables

3.1 Sample

The sample contains of securities listed on the major US stock exchanges New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ. Monthly returns are extracted from CRSP and S&P Long-Term Domestic Issuer Credit Rating is extracted from Compustat. Accounting data and other firm characteristics is gathered from Compustat. Fama-French, momentum and liquidity factors are downloaded from the Fama-French Portfolios and Factors database. Excess return on the market is gathered from the same source, which is calculated as the value-weight return on all NYSE, Amex, and NASDAQ stocks minus one-month Treasury bill rate. All the data above are available through Wharton Research Data Services (WRDS). The time period ranging from January 1985 to December 2013 with a total number of 3,172 securities and 311,525 observations that satisfies the criteria's below:

1. Be a valid link between Compustat and CRSP identifiers
2. Monthly returns, volume and shares outstanding available in the CRSP database
3. The security must be common stock (share code 10-11)
4. The security can be active or inactive
5. Long-term credit rating available in Compustat
6. Listed on NYSE, NASDAQ or AMEX
7. Data to compute Book-value of equity available in Compustat (total assets and total liabilities)
8. Available data about sector
9. Not classified as a financial firm

We merge CRSP and Compustat data. The link table available from CRSP is used to link the security's unique identifier in Compustat (GVKEY) with the unique identifier in CRSP (LPERMNO). Duplicates are investigated and removed when there are identical observations where security id, date, return, rating, fundamental values and stock exchanges are similar. Considering that the fundamentals are quarterly, the last known observation is used. Ratings that are classified as "Not meaningful" (NM), "Not reported" (NR), and selective default (SD) are dropped. We are dropping 48 observations due to missing information about sector.

Securities classified as financial firms are excluded from the analysis because of their complex and distinctive balance sheets. In addition financial firms are highly leveraged, which for nonfinancial firms more likely indicate financial distress (Fama and French, 1992, Banz, 1981, Avramov et al., 2009)

To analyze whether the effect differs over the business cycle or not, data is gathered from the National Bureau of Economic Research (NBER). NBER's Business Cycle Dating Committee maintains a chronology of the U.S business cycle, and consists of alternating dates of peaks and troughs in economic activity. A period between a peak and a through is defined as a recession, and a period between a through and a peak is defined as an expansion. The dates are provided in Table 2.

Table 2
NBER's Business Cycle Chronology

		Duration in months			
Peak month	*Trough month*	*Peak to Trough*	*Trough to Peak*	*Peak to Peak*	*Trough to Trough*
July 1981	November 1982	16	12	18	28
July 1990	March 1991	8	92	108	100
March 2001	November 2001	8	120	128	128
December 2007	June 2009	18	73	81	91

Source: (NBER, 2014)

Further we define two types of events, downgrades and upgrades. Since we are using monthly data, it's difficult to get an accurate time of when the event occurred. It is therefore logical to assume that the time the security either gets downgraded or upgraded is the first month with new rating.

3.2 Variables

Describing the relationship between stock return and one or several factors is difficult because there is a lot of noise in the equity markets. As discussed under literature review, several papers shows that certain factors contribute to explain stock returns more than others. These variables will hereby be called control variables. In deciding which firm characteristics to include as possible determinants of expected returns, attention was given to those variables that had been found to be important in prior studies. We include firm size measured by market value of equity (Banz, 1981, Fama and French, 1992, Fama and French, 1993). Book-to-market equity is also proven to show strong association with average returns (Fama and French, 1992). Liquidity is also shown to explain returns (Brennan et al., 1998) . We will apply share turnover as in (Avramov et al., 2009) as a measure of liquidity. Controlling for factors that earlier have proven to contribute to describe stock returns are included to improve the efficiency of the estimates of the coefficients of the other variables.

Credit rating is S&P Domestic Long Term Issuer Credit Rating (see section 2.2 for a more detailed explanation). We transform the ratings to a numerical value, where 1 represents AAA rating and 22 represents D rating, following Avramov et al. (2009). Hence, the higher numerical value, the worse credit rating. This is the main testing variable.

Return is monthly return adjusted for dividends, and stock splits as reported in CRSP. Monthly return is by CRSP calculated by the following formula:

$$ret_t = \left[\frac{p_t \times f_t + d_t}{p_{t-1}}\right] - 1 \qquad \text{Equation 1}$$

where:

ret_t is the holding period return at time t

p_t is the last sale price or closing bid/ask average at time

p_{t-1} is the sale price or closing bid/ask average at time of last available price<t this is usually one period before t, but t can be up to ten periods before t if there are non valid prices in the interval.

f_t is the price adjustment factor at time t

d_t is the cash adjustment factor at time t

Due to some of the securities have delisted in the period we will use delisting return whenever a firm has delisted. To calculate delisting return we follow WRDS and Beaver et al. (2007):

$$DRet_t = (1 + ret_t)(1 + dr_t) - 1 \qquad \text{Equation 2}$$

Through the thesis when we are talking about return, return includes delisting returns.

Market value of the equity (ME) is calculated as the number of shares outstanding multiplied with the closing price adjusted for dividends and stock splits. Furthermore, we use the natural logarithm of ME, LOG (ME), as an explanation variable in the model with different lead and lags. Logarithms are applied because the variable shows a considerable skewness.

Book value of equity (BE) is computed as total assets minus total liabilities. The data from Compustat is only available quarterly. To deal with this we have used the last available quarter for subsequent months. For instance, the book value in December is used as a proxy for the book value in January and February in the following year, the book value per March is used as a proxy for book value in April and May etc.

Book-to-market (BTM) is the ratio between book value of equity and market value of equity. In our model we have used the natural logarithm of BTM, LOG (BTM). Logarithms are applied because the variable shows a considerable skewness.

Share turnover (TO) is calculated as the total number of shares traded over a period (volume) divided by shares outstanding in that period. This is a measure of the equity liquidity. The higher turnover the more liquid the stock is. Logarithms are applied, and we denote the variable LOG (TO).

As in Avramov et al. (2009) we apply two lags to LOG (ME), LOG (BTM) and LOG (TO). For an overview over all variables, and their associated calculation and sources see appendix 1.

3.3 Descriptive statistics

3.3.1 Comparing non-rated stocks with rated stocks

To begin with, it may be useful to see if there is any difference between securities that are rated and those who are not rated. Table 3 presents descriptive statistics on the key variables. The full sample contains of data that qualifies to the criteria's mentioned initially, except for the rating criteria. We divide it into two subsamples: Rated securities[3] and not rated securities. We report arithmetic mean, standard deviation (std. dev.) and the number of observations (N). Not surprisingly, the rated securities are on average larger measured by market value than non-rated securities. This may be because larger companies are more dependent/benefits upon being rated. As mentioned earlier, the rating process is a costly effort, and it is required to get access to a broad investor base, reputed name and higher bargaining power over banks, among other reasons. The same pattern is seen again when looking at the book values.

[3] This is not the final sample that satisfies all the criteria's above and contains unbalanced data (e.g. there might be missing a return observation for a rating observation).

However, there is a higher variation among the rated stocks. Rated securities also appear to have higher volume measured by million dollars, and share turnover. One consequence of the difference between rated and non-rated securities is that the results of the further analysis may not be applicable to all securities. Moreover, the securities that are not rated are overweight as opposed to rated securities, which can influence the conclusion. In the rest of the thesis all numbers provided are from the final sample, which is described in the following Table 4.

Table 3
Comparing the full sample, rated, and non-rated securities

	Mean			Std. Dev.			Number of obs.		
Variables	Full	Rated	Not Rated	Full	Rated	Not Rated	Full	Rated	Not Rated
Return (Ret)	1.2%	1.1%	1.2%	0.204	0.216	0.207	1,596,867	311,874	1,284,993
Credit Rating	10.31	10.31	-	3.8	3.8	-	313,533	313,533	
Market-Value of Equity (ME)	1,678	6,769	451	10,656	3,866	3,578	1,609,231	312,462	1,296,769
Assets - Total	1,846	7,528	403	11,878	2,476	3,102	1,544,574	312,837	1,231,737
Liabilities - Total	1,207	5,047	231	9,234	1,958	2,697	1,543,518	312,835	1,230,683
Book-Value of Equity (BE)	637	2,481	169	3,551	875	825	1,543,474	312,835	1,230,639
Book-to-Market (BTM)	0.68	0.59	0.70	3.86	3.36	3.55	1,530,639	311,764	1,218,875
Volume NASDAQ	166	1,020	106	1,930	1,020	1,633	1,014,252	67,036	947,216
Volume NYSE/AMEX	412	866	94	1,535	2,256	433	594,966	245,426	349,540
Shares Outstanding	54	181	23	260	97	90	1,620,625	313,434	1,307,191
Turnover NYSE/AMEX (TO)	0.10	0.13	0.08	0.15	0.14	0.14	597,765	246,017	351,748
Turnover NASDAQ (TO)	0.13	0.21	0.13	0.34	0.35	0.35	1,021,864	67,404	954,460

ME, Assets, Liabilities, BE, and volume are measured in million dollars. Shares outstanding is the number of shares recorded in millions.

3.3.2 Final sample

Table 4 reports the time-series average of the cross-sectional means of the raw data. Average monthly return is 1.1% and the volatility (Std. Dev. is 0.14). The average credit rating is approximately BBB-. The size of the companies represented by ME is varying from $0.15 billions to $602.4 billions, averaging $6.78 billions. On average, the firms have a BE of 2.5 billions. BTM averages at a ratio on 0.59. Trading volume, measured by million dollars is on average higher on NASDAQ than on NYSE/AMEX. As a natural consequence of this NASDAQ stocks have on average a higher turnover than NYSE/AMEX stocks. This can be a measure on liquidity, hence we can say that NASDAQ stocks are more liquid compared to NYSE/AMEX stocks.

The time-series average of the cross-sectional means of the variables used in the regression analysis is presented in Table 5. Notice we have transformed Market-Value of Equity, Book-to-market and Turnover to logarithmic values.

Table 4
Descriptive statistics

Variables	Mean	Std. Dev.	N
Return (Ret)	1.1%	0.140	311,525
Credit Rating	10.3	3.8	311,525
Market-Value of Equity (ME) ($mill)	6,782	22,177	311,525
Assets – Total ($mill)	7,546	25,185	311,525
Liabilities – Total ($mill)	5,058	19,709	311,525
Book-Value of Equity (BE) ($mill)	2,488	7,423	311,525
Book-to-Market (BTM)	0.59	5.38	311,525
Volume NASDAQ ($mill)	1,025	4,235	66,645
Volume NYSE/AMEX ($mill)	866	2,258	244,880
Shares Outstanding (#mill)	182	539	311,525
Turnover NYSE/AMEX (TO)	0.13	0.16	311,525
Turnover NASDAQ (TO)	0.21	0.24	244,880

Table 5
Descriptive statistics – testing variables

Variables	Mean	Std. Dev.	N
Return (Ret)	0.011	0.140	311,525
Credit Rating	10.3	3.8	311,525
LOG (ME_{t-2}))	7.20	1.82	310,315
LOG (BTM_{t-2})	-0.66	0.84	295,957
LOG (TO_{t-2})	-2.40	1.05	310,317

Continuing describing the sample Table 6 represents an overview over the observations per stock exchange and the sector distribution based on Global industry Classification Standard (GICS). The first column represents number of observations, and the second column show column % of the total. Panel A shows that NYSE is the dominating stock exchange with 74.8 % of the observations, followed by NASDAQ (21.4%) and AMEX (3.8%). Investment grade stocks contribute to 51.5% of the observations while speculative grade stocks contribute to

48.5 % of the observations. Furthermore, we observe that there are very few observations in the rating categories CCC to D, especially in the C category.

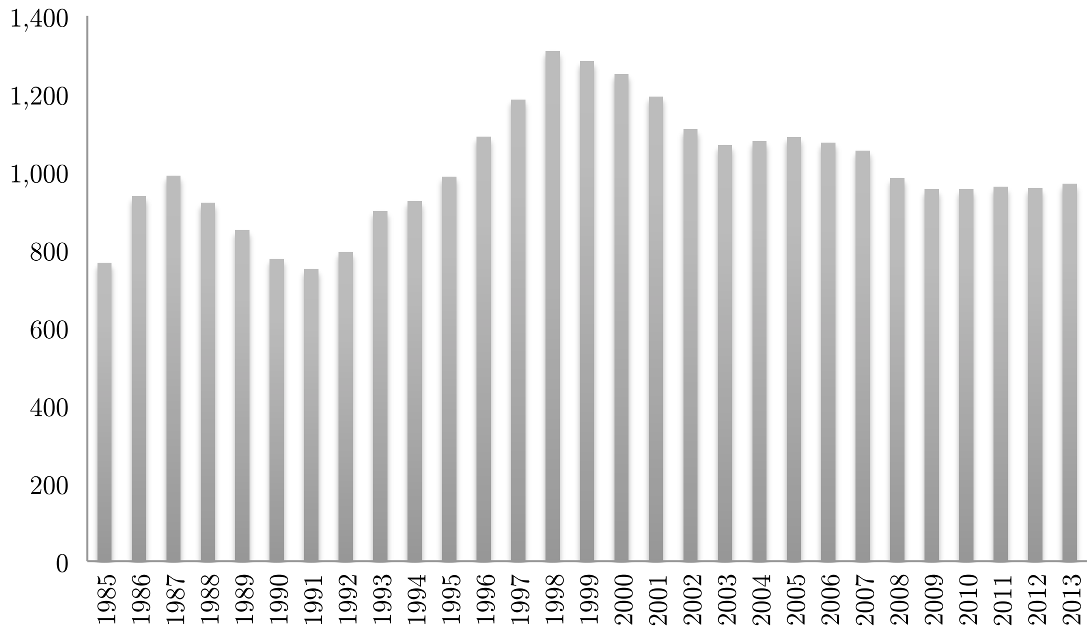
In Panel B we observe that Consumer Discretionary is the biggest sector represented in the sample (23.6%) followed by Industrials (18.4%) and Materials (10.4%). The distribution does not vary much between stock exchanges except for information technology, which is one of the dominating sectors on NASDAQ.

Table 6
Observations per stock exchange and GIC sector

	Exchange							
	NYSE		**AMEX**		**NASDAQ**		**Total**	
	No	Col %	No	Col %	No	Col %	No	Col %
Panel A: Credit Rating								
AAA	3,121	1.3	0	0.0	268	0.4	3,389	1.1
AA+	1,366	0.6	0	0.0	107	0.2	1,473	0.5
AA	6,533	2.8	25	0.2	379	0.6	6,937	2.2
AA-	6,706	2.9	0	0.0	604	0.9	7,310	2.3
A+	12,935	5.5	121	1.0	1,184	1.8	14,240	4.6
A	22,762	9.8	501	4.3	1,637	2.5	24,900	8.0
A-	17,596	7.5	305	2.6	1,960	2.9	19,861	6.4
BBB+	21,481	9.2	350	3.0	1,872	2.8	23,703	7.6
BBB	29,284	12.6	537	4.6	3,190	4.8	33,011	10.6
BBB-	22,378	9.6	599	5.1	2,524	3.8	25,501	8.2
BB+	15,111	6.5	1,034	8.8	2,379	3.6	18,524	5.9
BB	19,700	8.4	477	4.1	6,240	9.4	26,417	8.5
BB-	20,863	8.9	1,453	12.4	12,142	18.2	34,458	11.1
B+	17,894	7.7	2,770	23.6	14,849	22.3	35,513	11.4
B	8,058	3.5	1,815	15.5	8,965	13.5	18,838	6.0
B-	4,050	1.7	594	5.1	4,996	7.5	9,640	3.1
CCC+	1,385	0.6	356	3.0	1,775	2.7	3,516	1.1
CCC	640	0.3	267	2.3	937	1.4	1,844	0.6
CCC-	286	0.1	182	1.6	151	0.2	619	0.2
CC	302	0.1	55	0.5	153	0.2	510	0.2
C	0	0.0	12	0.1	2	0.0	14	0.0
D	708	0.3	268	2.3	331	0.5	1,307	0.4
Total	233,159	100.0	11,721	100.0	66,645	100.0	311,525	100.0
Panel B: GIC Sectors								
Energy	23,867	10.2	1,238	10.6	2,774	4.2	27,879	8.9
Materials	28,353	12.2	723	6.2	3,257	4.9	32,333	10.4
Industrials	44,642	19.1	2,129	18.2	10,518	15.8	57,289	18.4
Consumer Discretionary	51,044	21.9	3,741	31.9	18,864	28.3	73,649	23.6
Consumer Staples	20,408	8.8	817	7.0	4,102	6.2	25,327	8.1
Health Care	18,089	7.8	1,190	10.2	8,407	12.6	27,686	8.9
Information Technology	14,692	6.3	1,015	8.7	11,986	18.0	27,693	8.9
Telecommunication Services	4,480	1.9	620	5.3	4,670	7.0	9,770	3.1
Utilities	27,584	11.8	248	2.1	2,067	3.1	29,899	9.6
Total	233,159	100.0	11,721	100.0	66,645	100.0	311,525	100.0
Sample size	233,159		11,721		66,645		311,525	

The number of distinct securities in the sample is on average 1128 per year, starting out with 765 in 1985, a maximum of 1308 in 1988 and 968 in 2013. In the whole sample there are in total 3,172 distinct firms. The distribution of securities is shown in Figure 4.

Figure 4
Numbers of securites per year



In Table 7 the average cross-sectional correlation between the variables used in the analysis is shown. We notice that rating is highly correlated with the lagged ME variable, and also noticeable correlated with the lagged BTM and TO variables. We should be aware of this since it can indicate multicollinearity. This topic is discussed later.

Table 7
Correlation between variables

Variables	Return (Ret)	Rating	LOG (ME_{t-2})	LOG (BTM_{t-2})
Return (Ret)	1.00			
Credit Rating	-0.01			
LOG (ME_{t-2})	-0.01	-0.63		
LOG (BTM_{t-2})	0.03	0.22	-0.45	
LOG (TO_{t-2})	-0.01	0.21	0.25	-0.17

4. Methododology

4.1 Panel data

The data set in this thesis can be classified as longitudinal data. Longitudinal data, or panel data, consists of time series for each cross-sectional member in the sample. One of the key feature of panel data is that the same cross-sectional units are followed over a given time period, and are including both a time serie and a cross-sectional dimension. Benefits observing the same units over time are that we can control for certain unobserved characteristics of the members, and it often allow us to study the importance of lags in behavior or the result of decision making (Wooldridge, 2008). However, we cannot assume that the observations are independently distributed across time. Unobserved factors that affect a firm's return in one year may also affect that firm's return in another year (Wooldridge, 2008). Special models and methods have been developed to deal with this challenge, and will be further explained in this chapter.

4.2 Empirical strategy

To test the hypothesis we use a quantitative approach. In the first part we form ten portfolios sorted by the level of credit rating. The reason for doing this is to get an understanding of what typically characterizes high-rated and low-rated firm. It also allows us to take into consideration that the distribution of rating is uneven in the right tail. Arithmetic mean and median values are computed for return, several firm characteristics, and alpha values and beta coefficient according to CAPM and Fama & French. The goal is to get a deeper understanding before testing on individual securities in the second part.

In the second part we run panel data regressions on individual securities by multiple regressions. The following model is assumed to be the best explanation.

$$Ret_{it} = \beta_1 rating_{it} + \beta_2 \log{(ME)}_{i,t-2} + \beta_3 \log{(BTM)}_{i,t-2} + \beta_4 \log{(TO)}_{i,t-2} + \varepsilon$$

As mentioned earlier market value of equity, book-to-market ratio and liquidity are proven to describe stock returns, and therefore included as control variables. The goal here is to see if there exist any causality between the dependent variable return, and the explanatory variable rating holding other variables fixed. This is often referred to as "ceteris paribus". Woolridge (2010) emphasize that the choice of control variables can influence the outcome.

Along the way there are also some pitfalls to consider. First of all it is difficult to isolate the effect of rating and equity returns. It exists a lot of noise in the equity market and returns are not only driven by fundamental factors, but also a lot of speculations, anomalies, expectation, and mood among the participants. We will control for several factors that previously are shown to explain equity returns to account for this problem. Second, we cannot for sure know that return follows rating or reverse. This is in econometric literature referred to as reverse-causality. In theory, credit ratings are forward looking and seek to be stable over business cycles, and short-term performance is disregarded. However, we cannot for sure know if a credit rating changes as a result of bad performance over a period of time. Remember back on the section about moral hazard. CRAs can adjust credit ratings after issue, if the issuers act irresponsible. To test for this we run a regression with lagged rating variable, which also serves as a robustness test. Third, the validity of the results relies on strict assumptions about the data set and statistical properties, which we deal with later in this chapter.

4.2.1 Forming decile portfolios

We are forming portfolios based on a certain criteria as in most other asset pricing studies (Avramov et al., 2009, Fama and French, 1992, Fama and French, 1993, Fama and French, 1996). Each month we rank the rated stocks, and sort them into 10 deciles. This process creates 3460 portfolios. Lastly we are averaging through all of these portfolios based on deciles, forming 10 portfolios that ranges from the best to worst rated stocks.

4.2.2 Panel data models

Multiple Regression

To test for ceteris paribus effect, multiple regression analysis is conducted in this thesis. One of the advantages over simple regression is that it allows us to explicitly control for many other factors that simultaneously affect the dependent variable. It's therefore more suitable for ceteris paribus analysis (Wooldridge, 2008). The general model is shown in Equation 3.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_k x_k + u, \qquad \text{Equation 3}$$

Where

y is the dependent variable

x is the independent variable

β_0 is the intercept

β_k measures the change in y with respect to x_k, holding other factors fixed.

u is the error term, and contains other factors than x affecting y.

We will have to make assumptions about how u is related to the independent variables. This can be stated in terms of a conditional expectation:

$$E(u|x_{1,}x_2, \ldots, x_k) = 0 \qquad \text{Equation 4}$$

Equation 4 requires at a minimum that all factors in the unobserved error term must be uncorrelated with the independent variables and have mean zero (Wooldridge, 2008, Woolridge, 2010). It also means that we have correctly accounted for the functional relationships between the dependent and independent variables (Wooldridge, 2008).

Estimators

Above we discussed in general the multiple regression model. The following section is about how we estimate the parameters in the model. There is a range of different methods, all with their strengths and weaknesses. First we will present the well-known ordinary least squares (OLS). Next we present fixed effects and random effects. They explicitly contain a time-constant unobserved effect, which we treat as random variables drawn from the population in line with the observed explained and explanatory variables. Last we explain the Fama-MacBeth procedure, which is an embraced method in asset pricing literature.

Ordinary least squares estimates (OLS)

OLS is an often-used procedure to estimate the parameters in the regression model. Without going to much in detail (for more information see for example (Wooldridge, 2008)) will provide some of the basic equations and assumptions behind the estimates. Understanding the logic behind is extremely important for the understanding of the regression results and interpretation. Further OLS provide a bridge between the other models we use later.

OLS minimize the sum of squared residuals to estimate the parameters in the regression equation. In the general form we pursue to estimate $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k$in Equation 5.

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_k x_k \qquad \text{Equation 5}$$

The OLS estimates, k+1 of them, are chosen to minimize the sum of squared residuals:

$$\sum_{i=1}^{n}(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \dots + \hat{\beta}_k x_{ik})^2 \qquad \text{Equation 6}$$

Using multivariable calculus the minimization problem is solved, which leads to k+1 linear equations in k+1 unknowns $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_k$:

$$\sum_{i=1}^{n} x_{ik}(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \dots + \hat{\beta}_k x_{ik}) \quad = 0 \qquad \text{Equation 7}$$

Equation 5 is called the OLS regression line, and after that is estimated we can obtain a predicted value for each observation.

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \dots + \hat{\beta}_k x_{ik} \qquad \text{Equation 8}$$

This is the predicted value obtained by plugging values of the independent variables for observation i into equation 8. Usual, the actual y_i will not equal the predicted value $\hat{y}_i$ because OLS minimize the average squared prediction error. The residual $\hat{u}_i$ is defined as,

$$\hat{u}_i = y_i - \hat{y}_i \qquad \text{Equation 9}$$

If $\hat{u}_i > 0$ ($\hat{u}_i < 0$), it means that y_i is under predicted (over predicted).

The OLS fitted values and residuals have some important properties:

1. The sample average of the residuals is zero and so $\bar{y} = \bar{\hat{y}}$
2. The sample covariance between each independent variable and the OLS residuals is zero. Consequently, the sample covariance between the OLS fitted values and the OLS residuals are zero.
3. The point $(\bar{x}_1, \bar{x}_2, \dots. \bar{x}_k, \bar{y}\ )$ is always on the OLS regression line: $\bar{y} = \hat{\beta}_0 + \hat{\beta}_1 \bar{x}_1 + \hat{\beta}_2 \bar{x}_2 + \dots + \hat{\beta}_k \bar{x}_k$.

Providing efficient and unbiased estimators we assume the following conditions:

1. Linear in parameters
2. Random sampling

3. No perfect collinearity
4. Zero conditional mean
5. Homoscedasticity (error terms equal variance)
6. Normality

The first four assumptions state that the OLS estimators are unbiased. Including assumption 5, we can aslo say that estimation of standard errors is unbiased. Given these assumptions, the OLS estimators will provide "Best Linear Unbiased estimators" (BLUE). It is rare, especially with a sample that is not random. If the assumptions are not met, we know that the results can be characterized by biased estimates of the coefficients, and in particular for the standard errors of the regression. Including the 6th assumption, normality, we get what we call the Classical linear model (CLM) assumptions (Wooldridge, 2008).

How we deal with some of the violations of the assumptions is explained in section 4.3

Fixed effects (FE) and Between effects estimation (BE)

The fixed effects estimation is using a transformation to remove the unobserved effect a_i prior to estimation. Any time-constant explanatory variables are removed along with $a_{i.}$ To understand how the fixed effect estimator works, consider the following model with a single explanatory variable for each i (Wooldridge, 2008),

$$y_{it} = \beta_1 x_{it} + \alpha_i + u_{it}, \quad t = 1,2, \ldots, T. \qquad \text{Equation 10}$$

For each i, we average this equation over time and get:

$$\bar{y}_i = \beta_1 \bar{x}_i + \alpha_i + \bar{u}_i, \qquad \text{Equation 11}$$

where $\bar{y}_i = T^{-1} \sum_{t=1}^{T} y_{it}$ and so on. For the reason that α_i appears in both equation xx and xx, and is fixed over time, we subtract Equation 11 from Equation 10 and gets:

$$\ddot{y}_{it} = \beta_1 \ddot{x}_{it} + \ddot{u}_{it}, \quad t = 1,2, \ldots, T. \qquad \text{Equation 12}$$

where $\ddot{y}_{it} = y_{it} - \bar{y}_t$ is the time-demand data on y, and similarly for $\ddot{x}_{it}$ and $\ddot{u}_{it}$.

We can also add more dependent variables to this model, which changes the equation to

$$y_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + \ldots + \beta_k x_{itk} + \alpha_i + u_{it}, \quad t = 1,2, \ldots \qquad \text{Equation 13}$$

And we get

$$\ddot{y}_{it} = \beta_1 \ddot{x}_{it1} + \beta_1 \ddot{x}_{it2} + \cdots + \beta_k \ddot{x}_{itk} + \ddot{u}_{it}, \quad t = 1,2,\dots,T. \qquad \text{Equation 14}$$

Notice that the unobserved effect a_i has disappeared. This suggests that we should estimate the last equation by pooled OLS. "A pooled OLS that is based on the time-demand variables is called the fixed effects estimator or the within estimator" (Wooldridge, 2008).

The fixed effects estimator is unbiased under a strict exogeneity assumption on the explanatory variables, that the idiosyncratic error u_{it} should be uncorrelated with each explanatory variable across all time periods. The other assumption needed for a straight OLS analysis to be valid is that the errors u_{it} are homoscedastic and serially uncorrelated (Wooldridge, 2008).

By running the OLS estimation on Equation 11 we obtain the **between estimator**. Notice that equation 11 does not include a time serie and the between estimator only consider variation between variables, and ignores information on how the variables change over time. Though it is interesting to see it in relation with the other estimation methods and to analyze how variables change across, in our case, firms.

Random effects estimation (RE)

The random effects estimator is attractive when we think the unobserved effect is uncorrelated with all the explanatory variables. Any leftover neglected heterogeneity only induces serial correlation in the composite error term. (Wooldridge, 2008). The random-effects model turns out to be a matrix-weighted average of the between-effects model and the fixed-effects model, and utilize both the cross-sectional dimension (between effect) and time series dimension (fixed effect).

Following Wooldridge (2008) we start with a unobserved effects model,

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \ldots + \beta_k x_{itk} + \alpha_i + u_{it}, \qquad \text{Equation 15}$$

When we assume that the unobserved effect α_i is uncorrelated with each explanatory variable it becomes a random effect model. The assumptions is the same as the fixed effects model, including that α_i is uncorrelated with each explanatory variable.

Fama-MacBeth procedure (FM)

Another well-established model, which is used in several papers (such as: (Banz, 1981), (Fama and French, 1992), (Brennan et al., 1998), (Avramov et al., 2009)) , is the Fama-MacBeth two-step regression (Fama and MacBeth, 1973). In the first step, for each single time period a cross-sectional regression is performed. In the second step, the final coefficient estimates are obtained as the average of the first step coefficient estimates.

In contrast to estimating a single cross-sectional regression with the sample averages, the Fama-MacBeth procedure involves running cross-sectional regression at each time period, i.e., (Cochrane, 2005)

$$R_t^{ei} = \beta_i' \lambda_t + \alpha_{it,} \quad i = 1,2,\dots,N \; for\; each\; t \qquad \text{Equation 16}$$

We show the algebra using one variable as in Cochrane (2005).

λ and α_i are then estimated as the average of the cross-sectional regression estimates,

$$\hat{\lambda} = \frac{1}{T}\sum^{T} \hat{\lambda}_t \qquad \text{Equation 17}$$

$$\hat{\alpha}_i = \frac{1}{T}\sum^{T} \hat{\alpha}_{it} \qquad \text{Equation 18}$$

Fama and Macbeth suggest that to generate the sampling errors for these estimates, we use the standard deviation of the cross-sectional regression estimates,

$$\sigma^2(\hat{\lambda}\ ) = \frac{1}{T^2}\sum^{T} (\hat{\lambda}_t - \hat{\lambda})^2 \qquad \text{Equation 19}$$

$$\sigma^2(\hat{\alpha}_i) = \frac{1}{T^2}\sum^{T} (\hat{\alpha}_{it} - \hat{\alpha}_i)^2 \qquad \text{Equation 20}$$

The Fama-MacBeth procedure uses the variation in the statistic $\hat{\lambda}_t$ over time to deduce its variation across samples (Cochrane, 2005). Cochrane (2005) explain that it is an intuitively appealing procedure because sampling error is "..about how statistic would vary from one sample to the next if we repeated the observations" (p. 246). Instead of deducing sampling variance of the sample mean of a series x_t by looking at the variation of x_t through time in the sample, Fama-MacBeth applies this idea to the slope and pricing error estimates. The formulas above suppose that the time series is not autocorrelated. Usually, asset returns are not highly correlated. However, we compute Newey-West heteroskedasticity and autocorrelation consistent standard errors (Newey and West, 1987) to account for the possibility. Our data display heteroskedasticity, hence we need to correct the standard errors.

Next, we test whether all the pricing errors are jointly zero suing this sampling theory. α is the vector of pricing errors acress assets. The covariance matrix of the sample pricing erros could be estimated by:

$$\hat{\alpha} = \frac{1}{T}\sum^{T} \hat{\alpha}_t \qquad \text{Equation 21}$$

$$cov(\hat{\alpha}) = \frac{1}{T^2}\sum^{T} (\hat{\alpha}_t - \hat{\alpha})\ (\hat{\alpha}_t - \hat{\alpha})' \qquad \text{Equation 22}$$

and then use the test in Equation 23,

$$\hat{\alpha}' cov(\hat{\alpha})^{-1}\hat{\alpha} \sim X^2_{N-1} \qquad \text{Equation 23}$$

Also, the Fama-MacBeth procedure allows changing betas (allows more heterogeneity in beta), which a single unconditional cross-sectional regression or a time-series regression test cannot easily handle (Cochrane, 2005).

Which procedure do we choose?

The methodology of Fama-MacBeth seems a bit different from “standard” methods. We can ask ourselves whether the procedure gives better results than the other methods.

In our dataset we have observations of N firms and time-series observations for each firm T. A pooled OLS will stack the i and t observations together and estimate β. What might be a problem here, is that the error terms are most likely cross-sectionally correlated at a given time (Cochrane, 2005). Referring to the CLM assumption above, OLS is still consistent. However, the OLS distribution theory is wrong and suggests that standard errors are too small. Hence, we must include corrected standard errors. The Fama-MacBeth procedure on the other side provides standard errors corrected for cross-sectional correlation (Cochrane, 2005).

Petersen (2005) compares approaches of estimating standard errors in finance panel data sets. She found that in recently published finance papers, 34 % of the papers estimated both coefficients and standard errors using the Fama-MacBeth procedure and 31 % included dummy variables for each cluster (fixed-effects). Further, there are two common forms of dependence in finance application. A firm effect, where observations of a firm in different years are correlated, and a time effect where the residuals of a given year may be correlated across firms. The results show that in the presence of a fixed firm effect, OLS and Fama-MacBeth standard errors are biased downward. Only considering a time effect Fama-MacBeth procedure are more efficient than OLS estimates. The panel data models are controlling for unobserved heterogeneity when it's constant over time and correlated with the independent variables. The fixed effect model uses variation within securities over time. In other words, everything that is stable different between the securities does not influence the estimators, and the fixed-effect model uses the time-series information in the data. It is also worth mentioned the between-effects model, which on the other hand only uses the cross-sectional information in the data. The random-effects model turns out to be a matrix-weighted average of the between-effects model and the fixed-effects model.

Petersen (2005) also underscore that the firm effect are more important in corporate finance applications than in asset pricing test where the dependent variable is return and excess returns are serially uncorrelated. Hence, the downward bias will be less important in those applications. "This isn't surprising since the Fama-MacBeth technique was developed to account for correlation between observations on different firms in the same year, not to account for correlation between observations on the same firm in different years" (p. 14).

Based on Petersen's work and best practice we will use the Fama-MacBeth procedure as our main model. We will also focus on the between-effect model and fixed-effect model, because they can say something about the variation across securities and over time. Results from the other methods will also be reported, however, since the results are easy to obtain with a statistical program. This will serve two purposes: First, the researcher can compare results and have a more critical view. Second, and perhaps most importantly, it provides robustness that our results are not driven or influenced by a specific method.

4.3 Econometrical challenges

See in relation with Appendix 3, which provides a graphical presentation of the issues.

4.3.1 Sample selection

The sample contains missing values for both the dependent variable and the explanatory variables. The statistical software we are using is handling missing values when performing regressions. The question is if there are any statistical consequences of missing values. Wooldridge (2008) says it depends of why data are missing. If it is random, then the sample is simply reduced. It makes the estimators less precise, but it does not introduce any bias. In the most cases, we just ignore the observations that have missing information.

In a nonrandom sample missing data is more problematic. This can cause a sample selection bias. In our sample we are omitting observations where return and rating is not available. The issue is whether it is random or not, which observations that take missing values. Assumption 2 (CLR) is violated, however, under the Gauss-Markov assumptions (excluding nr.2) the sample can be chosen based on the independent variables without causing statistical problems. We have no reason to believe that the reason for missing values in our data set is not random.

4.3.2 Outliers and influential data

Analyzing the data shows potential outliers, especially in returns. Using monthly data may lead to drastic fluctuations. Figure 7 shows the plots of combinations of each of the variables used in the analysis. We see that return show some potential outliers that can influence the results. Removing the most influential data points does not make any differences to the results.

4.3.3 Heteroskedasticity

Homoscedasticity "..states that the variance of the unobservable error, u, conditional on the explanatory variables, is constant" (Wooldridge, 2008, p. 263). In a situation where the variance change across different segments, and the homoscedasticity assumption is violated, we have heteroskedasticity. In Appendix 3 we show a plot of residuals versus fitted value. Figure 9 and the Breusch-Pagan test for heteroskedasticity confirms that the data set displays a considerable heteroskedasticity. To deal with this particular issue, we apply robust standard errors.

4.3.4 Multicollinearity

Multicollinearity is a situation where there is a high, but not perfect correlation between two or more independent variables (Wooldridge, 2008). We can conduct a Variance Inflation Factor (VIF) analysis to test for the severity of multicollinearity. Often the cutoff value is a VIF above 10 to conclude that multicollinearity is a problem. Table 8 represents the VIF values, and we can conclude that multicollinearity is not a huge problem.

Table 8
Variance inflation factor (VIF)

Variable	VIF	1/VIF
LOG(ME_{t-2})	2.44	0.409278
Credit Rating	2.13	0.468981
LOG(TO_{t-2})	1.42	0.705588
LOG(BTM_{t-2})	1.27	0.789981
Mean VIF	1.81	

5. Empirical results

In the previous chapters we explained the theory, sample and methods that are used to test the research question. The first part of the analysis will provide analysis with a portfolio approach to get an idea of what results we can expect when running the analysis on individual securities. The second part will investigate in-depth the credit rating effect on individual securities. Panel data regressions are applied to examine the relationship between returns and credit rating, controlling for other firm characteristics that previously are shown to affect securities' return. In the end of the section we will discuss the findings.

5.1 Portfolio approach – an overview over security charachteristics by credit rating deciles

In this first part of the analysis we will give some perspective about the securities that is included in the sample. In this section we follow Avramov et al. (2009) and form decile portfolios each month based on the credit rating at time t. Cross-sectional mean and median characteristics are computed at time t (in contrast to (Avramov et al., 2009), who use time t+1).

Panel A in Table 9 presents mean (median) values for some firm characteristics. Credit rating is transformed to values ranging between 1-22, where 1 represents AAA and 22 represents D. Return is monthly holding period return adjusted for dividends and splits. Price is the closing price at the end of the month. Volumes and ME are reported in million dollars. At first glance we see that there is no clear pattern in returns for the seven first groups. The three worst deciles respectively show 1.056% (0.35%), 1.091% (0.00%), and 0.26% (-1.031%) average (median) monthly returns. The difference between portfolio 1 and portfolio 10 is 0.87 percentage points, and is statistically significant at the 5% level (t-value -6.04). ME consistently fall when credit rating deteriorates. This indicates we should expect that ME is lower among the worst rated securities than the best-rated securities. We also notice that book-to-market increase, as credit rating gets worse for the six first portfolios. The last deciles vary a bit, and the worst decile got -0.42 BTM. This indicates that the worst rated stocks have negative book value of equity. An explanation can be that book value of the most distressed firms is often completely wiped out by losses.

Table 9
Portfolios sorted on credit rating each month

Portfolio (N%)	1 (13%)	2 (10%)	3 (11%)	4 (8%)	5 (9%)	6 (10%)	7 (11%)	8 (9%)	9 (8%)	10 (7%)
Panel A: Arithmetic mean and median										
Credit rating	4.4	6.6	8.1	9.1	10.2	11.6	12.7	13.8	14.8	16.6
	(5)	*(7)*	*(9)*	*(9)*	*(10)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*
Return	1.135%	1.126%	1.169%	1.097%	1.152%	1.179%	1.239%	1.056%	1.091%	0.266%
	(1.083%)	*(1.174%)*	*(1.174%)*	*(1.064%)*	*(1.031%)*	*(0.860%)*	*(0.791%)*	*(0.355%)*	*(0.000%)*	*-(1.031%)*
Closing price	53.8	45.3	40.8	36.6	32.9	26.5	22.3	16.8	13.0	9.4
	(45.3)	*(38.6)*	*(34.1)*	*(30.7)*	*(27.5)*	*(21.8)*	*(17.8)*	*(13.2)*	*(8.8)*	*(5.0)*
Market-Value	29,561	9,148	6,355	4,246	3,086	2,082	1,318	930	905	570
	(9,908)	*(4,191)*	*(3,051)*	*(2,191)*	*(1,617)*	*(1,036)*	*(580)*	*(345)*	*(307)*	*(134)*
Book-To-Market	0.41	0.52	0.64	0.72	0.70	0.79	0.77	0.77	0.74	-0.42
	(0.35)	*(0.47)*	*(0.52)*	*(0.56)*	*(0.59)*	*(0.60)*	*(0.56)*	*(0.58)*	*(0.56)*	*(0.51)*
Total Liabilities/ME	0.7	0.9	1.3	1.2	1.4	1.9	2.3	3.2	4.4	12.1
	(0.44)	*(0.66)*	*(0.86)*	*(0.93)*	*(1.00)*	*(1.10)*	*(1.22)*	*(1.48)*	*(2.02)*	*(3.32)*
Share turnover	8.5%	11.4%	12.9%	14.3%	15.4%	17.1%	16.1%	17.4%	19.8%	21.6%
	(0.07)	*(0.08)*	*(0.10)*	*(0.10)*	*(0.10)*	*(0.11)*	*(0.11)*	*(0.11)*	*(0.12)*	*(0.11)*
Volume NYSE/AMEX $	2,370	1,140	863	693	535	418	304	241	290	200
	(710)	*(357)*	*(330)*	*(233)*	*(164)*	*(118)*	*(61)*	*(37)*	*(31)*	*(8)*
Volume NASDAQ $	*8,610*	*2,771*	*2,190*	*1,447*	*1,271*	*779*	*432*	*308*	*335*	*277*
Panel B: CAPM alpha and beta										
Alpha	0.35%	0.28%	0.42%	0.15%	0.26%	0.21%	-0.02%	-0.10%	-0.05%	-1.20%
Market	0.72	0.87	0.87	0.98	1.00	1.20	1.20	1.30	1.66	1.80
Panel C: Fama & French alpha and betas plus momentum factor										
Alpha	0.27%	0.17%	0.27%	0.09%	0.16%	0.22%	-0.14%	0.01%	0.06%	-0.74%
Market	0.81	0.91	0.92	1.01	1.07	1.15	1.22	1.21	1.40	1.41
SMB	-0.15	0.05	0.16	0.25	0.33	0.54	0.76	0.91	1.14	1.44
HML	0.30	0.30	0.43	0.48	0.52	0.60	0.53	0.42	0.16	0.29
Momentum	-0.04	0.00	-0.08	-0.13	-0.16	-0.28	-0.23	-0.39	-0.58	-0.66

Dichev (2009) explains a similar situation in his paper using bankruptcy risk as an explanatory variable. He says that "..even if firms with high bankruptcy risk have higher returns, the nonmonotonic relation between bankruptcy risk and book-to-market suggests that a distress explanation is unlikely to account for the book-to-market effect" (p. 1141). Substituting bankruptcy risk with credit rating, it can indicate that credit rating also is measuring distress risk. Considering trading volume the average dollar volume on NYSE/AMEX is lower than NASDAQ. We also observe gradual reduction in volume when credit rating gets worse, indicates that the best-rated stocks are more liquid than the worst rated stocks. Liabilities divided by ME shows a steadily increasing ratio as rating get worse, especially in the worst decile.

Panel B and C represents the numbers provided by the CAPM and Fama-French three factor regressions. Each portfolio is regressed with excess return (return minus risk-free rate) as dependent variable and the return of the market portfolio minus risk-free rate as the explanatory variable. For the Fama-French three factor model SMB, HML and momentum factor is included as explanatory variables in addition to excess return on the market. The alpha value tells you how the portfolio performed respectively to the CAPM and the Fama-French predicted returns. For the CAPM regressions the alpha value is positive in the six first deciles. For the four last it is negative, and stocks in the worst decile are on average earning -1.2 percentage points below the predicted returns. Another observation is that the beta of the portfolio increases from 0.72 to 1.80 in the worst decile (all strongly significant). This means that the securities in the worse deciles are more sensitive to systematic risk, because beta is larger than one. Considering the Fama-French regression we notice the same increase in market beta. Alpha is negative in the four last deciles. The SMB factor behaves as expected. An increasing factor means that there are smaller companies among the worst rated deciles. HML can be seen in relation with BTM. An increasing loading on the factor indicates a higher book-to-market ratio.

So what did we learn from this exercise? Among the highest rated firms we cannot see with the naked eye whether there is any pattern in returns. However, the three worst deciles show a lower return than the rest of the deciles, suggesting that there may be a negative relationship between return and credit rating. Especially the last decile shows significant lower returns. Furthermore, higher rated firms seem to have a higher market value, lower turnover, lower book-to-market, lower betas and higher alphas in contrast to lower rated firms. An interesting observation is the relatively high return, low beta stocks in the best deciles and the relatively low return, high beta stocks in the worse deciles. Holding other factors fixed an increase in beta should increase the expected return because the increased volatility against the market index. The positive alpha values among the best-rated deciles and the negative alpha values among the worst rated deciles, suggest that there may be something these models cannot explain.

In the extension of the analysis above we continue to investigate the overall characteristics from the portfolio approach. To get a deeper understanding we will now look at upgrades and downgrades. In the full sample we have 7,734 events, where 2,983 are upgrades and 4,751 are downgrades. A potential concern is that the number of observations in times of expansions is way bigger than in times of recessions, which can bias the numbers. Further it is logical that in the best deciles it requires a larger threshold to be upgraded rather than downgraded.

Calculating downgrades in percent of the total number of events, we observe a higher downgrade-percent during recessions than expansions. The average size of a downgrade or upgrade is somewhat ambiguous.

Table 10
Portfolios sorted on credit rating - Upgrades and Downgrades.

Portfolio	1 (13%)	2 (10%)	3 (11%)	4 (8%)	5 (9%)	6 (10%)	7 (11%)	8 (9%)	9 (8%)	10 (7%)
Panel A Full Sample										
Upgrade	96	159	225	282	339	367	394	427	269	425
Downgrade	484	461	414	356	425	473	440	560	391	747
Downgrades in %	83%	74%	65%	56%	56%	56%	53%	57%	59%	64%
Average size of downgrades	1.54	1.53	1.54	1.48	1.53	1.51	1.52	1.64	2.05	2.71
Average size upgrades	1.11	1.11	1.18	1.13	1.33	1.24	1.38	1.31	1.30	1.93
Panel B Recessions										
Upgrade	5	11	16	20	43	30	24	27	19	29
Downgrade	60	62	75	43	91	94	47	119	119	157
Downgrades in %	92%	85%	82%	68%	68%	76%	66%	82%	86%	84%
Average size of downgrades	1.40	1.29	1.48	1.47	1.24	1.36	1.66	1.67	2.09	2.76
Average size upgrades	1.20	1.00	1.12	1.10	1.42	1.10	1.21	1.00	1.11	1.41
Panel C Expansions										
Upgrade	91	148	209	262	296	337	370	400	250	396
Downgrade	424	399	339	313	334	379	393	441	272	590
Downgrades in %	82%	73%	62%	54%	53%	53%	52%	52%	52%	60%
Average size of downgrades	1.56	1.57	1.55	1.49	1.60	1.55	1.50	1.63	2.03	2.70
Average size upgrades	1.11	1.12	1.18	1.13	1.31	1.25	1.39	1.33	1.32	1.97

Among the eight best deciles it is not much variation across portfolios and time. At the other end of the scale we notice a stronger magnitude of downgrades, which indicates that in the worst deciles firms on average are downgraded 2-3 steps down. The magnitude does not change much whether it is in recessions or expansions. Upgrades on the other hand, also have a stronger magnitude in the worst decile, and are on average 1.93, mostly explained by an average upgrade of 2 steps during expansions.

5.2 Regression analysis using individual securites

Moving over from the portfolio approach, we will now start considering the rating effect on individual securities. The analysis is basically based on panel data regressions to investigate weather there is a relationship between stock returns and corporate credit ratings. Results are reported using several methods to estimate the regression coefficients and test statistics. The reason for doing this is that each method has its strengths and weaknesses. To deal with heteroskedasticity and auto-correlation, results are reported using robust standard errors. Where it is appropriate we report autoregressive conditional heteroskedasticity (ARCH) models to deal with heteroskedasticity.

Based on the results from section 5.1 it is a bit vague what results we can expect from the regression analysis. We saw that the difference between the best and worst decile were significant, but among the best deciles there were not a clear pattern in returns. Theories on asset pricing, like CAPM, suggest that the return should be higher when the systematic risk increase. However, we observed that low beta stocks yielded higher returns than high beta stocks. We should expect ME to decrease as credit rating increase. BTM and TO should have a positive sign.

5.2.1 A negative relation between credit rating and stock returns

To begin with, Table 11 presents the regression results from FM, OLS, BE, RE, RE AR (1), FE and FE AR (1). Results presented in the text are based on FM-procedure unless otherwise clearly specified. Return is the dependent variable, credit rating the testing variable, and LOG (ME_{t-2}), LOG (BTM_{t-2}), and LOG (TO_{t-2}) control variables. We apply 2 lags on the control variables (Avramov et al., 2009). The sample is a bit lower than reported initially due to the use of lagged variables. All the estimator-methods show a negative relation between returns and credit rating. As in Avramov et al. (2009), using Fama-MacBeth regression we observe a negative and statistically significant coefficient on the 5% level on credit rating. This can be interpret as 1 notch worse credit rating will lead to 0.0083 basis point less monthly return. Log (ME_{t-2}) is negative and statistically significant at the 1% level, which is consistent with earlier studies. Log ($BTM_{t-2)}$ is positive but not statistically significant. Neither is Log (TO_{t-2}). The explanation power in our model R^2 is 6.5%, which is considered good in this kind of empirical study. In the cross-section, across securities, the effect is stronger and statistically significant at the 0.1 % level considering the BE-model. The FE (AR1)-model is statistically significant at the 10% level, and the negative credit rating coefficient has a weaker magnitude than the estimate provided by the BE-model. The results suggest that credit rating varies both over time and across securities. In contrast FM, OLS and RE use a combination of time and cross-sectional variation, and we can therefore conclude that credit ratings vary across and within securities.

Our results are robust against including financial firms and excluding stocks with a share price lower than one dollar, but with slightly lower coefficients. Using excess return as dependent variable yield the same result. The results are not reported.

Table 11
Regression results with the main model

	FM	OLS	BE	RE	RE AR(1)	FE	FE AR(1)
Credit Rating	-.00083*	-.0011***	-.0014***	-.0017***	-.0015***	-.00037	-.00032+
	(-2.50)	(-11.47)	(-4.12)	(-9.88)	(-12.65)	(-1.30)	(-1.66)
LOG (ME t-2)	-.0015**	-.0016***	.0028***	-.0074***	-.0032***	-.016***	-.016***
	(-2.76)	(-7.29)	(3.86)	(-18.93)	(-11.80)	(-21.98)	(-36.17)
LOG (BTM t-2)	.00045	.004***	-.0015	.0075***	.0055***	.0077***	.008***
	(0.51)	(8.89)	(-1.45)	(11.32)	(14.46)	(9.03)	(15.33)
LOG (TO t-2)	.00055	.0011***	-.0022*	.0011*	.0011***	.0018***	.0018***
	(0.71)	(3.55)	(-2.24)	(2.56)	(3.46)	(3.36)	(4.28)
Constant	.032***	.039***	-.00053	.085***	.055***	.14***	.14***
	(4.93)	(13.99)	(-0.06)	(18.70)	(16.44)	(20.48)	(30.47)
Observations	295951	295951	295951	295951	295951	295951	292831
R^2	0.065	0.001	0.041			0.010	

t statistics in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Return is the dependent variable. We run Fama-Macbeth, OLS, Between effects, Random effects and Fixed effects with and without autoregressive conditional heteroskedasticity. Fama-MacBeth standard errors are robust to disturbance that is heteroskedastic and autocorrelated using the Newey-West procedure. OLS, BE, RE and FE are robust to disturbance that is heteroskedastic, using Stata's robust option.

The results suggest that the worst rated firms on average earn lower returns, are smaller and have higher turnover than high rated firms. This is a puzzle, because according to economic theory investors demand a premium to bear risk. Instead, we observe an opposite relation between return and credit risk. Although the regressions suggest that there is a negative relation between credit rating and stock returns, we cannot exclude that it exist reverse causality between returns and rating in the reality. Analyst continuously monitoring firms should cause that information is reflected in stock prices. To check if there exist such reverse causality we perform the same regressions with lagged rating variables.

As we see from the FM regression results in Table 12, the negative effect is still persistent and statistically significant at the 10 % level with credit rating variable lagged t-2 and t-3. This suggest that reverse-causality effect may not exist, or in weak form. Including lead credit rating variable (F.1) we observe a higher magnitude and t-value. On the other hand, this might be evidence of reverse causality. Earlier we mentioned that CRAs are forward looking, and based on the evidence above it is hard to exclude a possible reverse causality effect.

Table 12
Regression results with lagged credit rating

	0	L.1	L.2	L.3	F.1
Credit Rating	-.00083**				
	(-2.64)				
L.1 Credit Rating		-.00048			
		(-1.55)			
L.2 Credit Rating			-.00065+		
			(-1.85)		
L.3 Credit Rating				-.00065+	
				(-1.86)	
F.1 Credit Rating					-.001**
					(-3.20)
LOG (ME t-2)	-.0015**	-.00092+	-.0011*	-.0011*	-.0019***
	(-2.85)	(-1.79)	(-2.01)	(-2.01)	(-3.65)
LOG (BTM t-2)	.00045	.00055	.00048	.00052	.00053
	(0.52)	(0.64)	(0.56)	(0.61)	(0.62)
LOG (TO t-2)	.00055	.00019	.00029	.00025	.00079
	(0.73)	(0.25)	(0.38)	(0.32)	(1.05)
[1em] Constant	.032***	.024***	.027***	.027***	.038***
	(5.22)	(3.87)	(3.76)	(3.69)	(5.99)
Observations	295951	292402	290275	286415	292150
R^2	0.065	0.068	0.070	0.070	0.067

t statistics in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Return is the dependent variable. We run Fama Macbeth regressions. Fama-MacBeth standard errors are robust to disturbance that is heteroskedastic and autocorrelated using the Newey-West procedure.

LOG (ME_{t-2}) is still statistically significant and the coefficient does not change much introducing lags.

To test the model's robustness we add and remove independent variables to see how the variables are influenced of a change in model specification. Of course, adding a variable will change the overall slopes of the regression results. Adding variables does not drastically the credit rating coefficients as noticed in Table 13. However, adding market value increase the magnitude and credit rating becomes significant. Remember the correlation in Table 7 where we observed a high correlation (-0.63) between credit rating and LOG (ME_{t-2}). This can raise problems involving multicollinearity. Testing the variance inflator factors for the independent variables, LOG (ME_{t-2}) has the highest VIF, 2.44. This is not alarming high, and it does not indicate problems with multicollinearity. The correlation between rating and market value may be so strong because, as we saw in Table 9, market value gradually decreased when credit rating worsened.

Table 13
Robustness test – stepwise inclusion of control variables

	1	2	3	4
Credit Rating	-.00031	-.00031	-.00026	-.00083*
	(-0.78)	(-0.84)	(-0.76)	(-2.50)
LOG (BTM t-2)		.0011	.00098	.00045
		(1.15)	(1.02)	(0.51)
LOG (TO t-2)			-.00019	.00055
			(-0.24)	(0.71)
LOG (ME t-2)				-.0015**
				(-2.76)
Constant	.014***	.014***	.014***	.032***
	(5.21)	(5.02)	(3.76)	(4.93)
Observations	311525	295957	295951	295951
R^2	0.035	0.049	0.061	0.065

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Return is the dependent variable. We run Fama Macbeth regressions. Fama-MacBeth standard errors are robust to disturbance that is heteroskedastic and autocorrelated using the Newey-West procedure.

5.2.2 Analyzing the credit rating effect over the business cycle

One of the contributions of this thesis is to analyze in depth the effect credit rating has on stock returns during business cycles. We should expect that during recessions the effect is stronger than during expansions due to a higher risk of financial distress. You can ask yourself if CRAs respond fast enough so that credit rating always mirrors the entity's capability to pay its obligations. Earlier we mentioned that long-term credit rating seek to be stable over the cycle and short-term disturbances, which can influence the results. To test the effect of rating during business cycles we generate a dummy variable bus, which takes value 0 if expansion, and 1 if recession. Next we generate a variable called busr, which is bus multiplied with rating. We include both of the variables in the model. The rationale for including both of the variables is because the business cycle in general may include effects that do not work through rating. Hence, to interpret busr correctly, which tell us something about how credit ratings interact with the business cycle, we must include bus in the model.

Table 14 presents the results using the FM-procedure, OLS, BE, RE and FE with autoregressive conditional heteroskedasticity. Return is the dependent variable, rating the testing variable, and LOG (ME_{t-2}), LOG (BTM_{t-2}), LOG (TO_{t-2}) control variables. In Panel B the same regressions is performed with a lagged rating variable as a robustness check. The sample is a bit lower than reported initially due to the use of lagged variables. Robust standard errors reported. We notice that the Fama-MacBeth method has omitted the two variables for busr. One reason for that might be that the Fama-MacBeth model runs cross-sectional regressions each month, and then averaging the coefficients from the first step. Therefor the first stage of the model omits them because it's impossible to include them in the cross sectional regression since they don't vary. The FM procedure will then produce the same results as in Table 11.

OLS, and RE show negative and statistically significant coefficients on the rating variable, almost with the same magnitude as in Table 11. The BE and FE display slightly lower coefficients, and the BE model is negative and strongly statistically significant at the 0.1% level. Considering the control variables LOG (ME_{t-2}), LOG (BTM_{t-2}), and LOG (TO_{t-2}), they are also consistent and strongly significant for the BE, RE, and FE models. In contrast to earlier, LOG (BTM_{t-2}) and LOG (TO_{t-2}) are now significant at the 0.1% level. The OLS regression has changed sign on the control variables, displaying a positive and significant LOG (ME_{t-2}), and negative and not significant LOG (BTM_{t-2}) and LOG (TO_{t-2}). In general, the OLS results look strange relative to the other estimation models. The difference can occur because OLS doesn't account for unobserved heterogeneity as the panel data models.

Considering the dummy variable bus, all the different method displays a negative coefficient. The BE and RE procedures show a negative and statistically significant coefficient in the range -0.0057 to -0.0074. Interpreting the results it means that, using the BE estimate, stocks earn on average 0.74% less return in times of recessions than expansions. The FE-procedure shows no significant coefficient, and a lower magnitude.

The busr variable is strongly significant at the 0.1% level and it doesn't vary much among the different methods, except for the OLS which is positive and not significant. The estimation of the busr coefficient is pretty consistent regardless of estimation procedure. Based on the results we can say that during recessions the differences between the credit rating categories become clearer. This support the hypothesis about that during times when financial distress becomes reality, the credit ratings become more important.

Again, lets consider the FE and BE coefficients on the credit rating, bus, and busr variable. In expansion there is still a cross-sectional effect between securities, and the coefficient is -0.00095 and strongly significant at the 0.1 % level. During recessions, considering the bus and busr coefficients, the effect is much stronger during recessions, both the business cycle itself and its interaction with rating. The FE-models does not confirm a credit rating effect over time in expansions. However, during recessions the busr variable is statistically significant at the 0.1 % level. Interpreting this observation indicates that the credit rating effect is stronger in recessions than in expansions, both over time and across securities.

Table 14
Regression result including a dummy for recessions

Panel A

	FM	OLS	BE	RE	RE AR(1)	FE	FE AR(1)
Credit Rating	-.00083**	-.0012**	-.00095***	-.0015***	-.0014***	-.00015	-.0001
	(-2.64)	(-3.03)	(-9.55)	(-9.01)	(-11.14)	(-0.52)	(-0.54)
LOG (ME t-2)	-.0015**	.004***	-.0014***	-.0071***	-.003***	-.016***	-.016***
	(-2.85)	(5.42)	(-6.42)	(-18.41)	(-11.26)	(-21.65)	(-36.72)
LOG (BTM t-2)	.00045	-.00024	.0049***	.0089***	.0067***	.0094***	.0097***
	(0.52)	(-0.23)	(11.12)	(13.63)	(17.56)	(10.91)	(18.61)
LOG (TO t-2)	.00055	-.0016	.002***	.0023***	.0021***	.0031***	.0032***
	(0.73)	(-1.59)	(6.19)	(5.17)	(6.37)	(5.83)	(7.45)
bus	0	-.079*	-.0074*	-.0057+	-.007**	-.0033	-.0033
	.	(-2.02)	(-2.35)	(-1.82)	(-2.78)	(-1.23)	(-1.29)
busr	0	.00089	-.0017***	-.002***	-.0018***	-.0023***	-.0023***
	.	(0.32)	(-4.71)	(-5.47)	(-7.75)	(-7.47)	(-9.82)
Constant	.032***	-.0034	.041***	.087***	.057***	.15***	.15***
	(5.22)	(-0.35)	(14.66)	(19.34)	(17.26)	(21.01)	(31.73)
Observations	295951	295951	295951	295951	295951	295951	292831
R^2	0.065	0.064	0.005			0.014	

Panel B

	FM	OLS	BE	RE	RE AR(1)	FE	FE AR(1)
L.1 Credit Rating	-.00048	-.00064***	-.00098*	-.00018	-.00086***	.0012***	.0012***
	(-1.55)	(-6.56)	(-2.00)	(-0.99)	(-6.83)	(4.35)	(6.31)
LOG (ME t-2)	-.00092+	-.00083***	.0036***	-.0093***	-.0023***	-.015***	-.015***
	(-1.79)	(-3.88)	(3.86)	(-20.81)	(-8.44)	(-20.57)	(-34.47)
LOG (BTM t-2)	.00056	.0048***	.0013	.0097***	.0068***	.0096***	.0097***
	(0.65)	(10.78)	(1.01)	(13.78)	(17.42)	(10.95)	(18.40)
LOG (TO t-2)	.00018	.0012***	-.00049	.0013**	.0012***	.0018***	.0018***
	(0.25)	(3.90)	(-0.39)	(2.83)	(3.57)	(3.38)	(4.28)
L.1 bus	0	-.0078*	-.05	-.0057+	-.0075**	-.0041	-.0037
	.	(-2.47)	(-1.00)	(-1.81)	(-2.94)	(-1.50)	(-1.45)
L.1 busr	0	-.00099**	-.0012	-.0014***	-.0011***	-.0016***	-.0017***
	.	(-2.69)	(-0.32)	(-3.76)	(-4.61)	(-5.14)	(-6.98)
Constant	.024***	.031***	.00014	.082***	.044***	.12***	.12***
	(3.87)	(11.16)	(0.01)	(16.58)	(12.98)	(18.12)	(26.46)
Observations	292398	292398	292398	292398	292398	292398	289351
R^2	0.068	0.003	0.035			0.013	

t statistics in parentheses

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Return is the dependent variable. We run Fama-Macbeth, OLS, Between effects, Random effects and Fixed effects with and without autoregressive conditional heteroskedasticity. Fama-MacBeth standard errors are robust to disturbance that is heteroskedastic and autocorrelated using the Newey-West procedure. OLS, BE, RE and FE are robust to disturbance that is heteroskedastic, using Stata's robust option.

5.2.3 Sector analysis

As previously mentioned default rates varied between sectors, which can indicate that investors awareness of credit ratings differs across sectors. Also typical sector characteristics, like asset intensive sectors, leverage, cyclicality etc., may play a role. Analyzing sectors will also serve as a robustness test to see if including dummy variables for each sector have any impact on the results. Moreover we seek to test if including sectors will yield a different result than not controlling for sectors.

In addition to including a dummy for each sector, gsector, a dummy for how each sector interacts with credit rating is included. We denote these dummy variables rgsector, which is the gsector dummy multiplied with the rating variable. To run the test properly, we need to omit one dummy to avoid perfect multicollinearity. Sector "Energy" is used as reference sector, hence the results reported show how each sector differs from "Energy".

Interpreting the Fama-MacBeth regression result in Table 15, credit rating is negative and statistically significant at the 5 % level. The coefficient is -0.0091 and has not changed much compared to the results in Table 11 (t-value 2.5, coefficient -0.0083). Same applies to the other procedures. LOG (ME_{t-2}) also shows a negative coefficient, and is highly significant. LOG (BTM_{t-2}) and LOG (TO_{t-2}) is still statistically insignificant. Considering the coefficient and significance level for the sector dummies (gsector), only Utilities show a negative and statistically significant coefficient at the 10% level. Among the rsector dummies no one are statistically significant. This means that the credit rating effect does not vary between sectors.

Compared with the other estimation models we observe some divergent results between the models. What we clearly observe is that the utility sector and industrials sector provides a lower return than the energy sector, with some significant results. Especially the utilities sector shows a considerable lower return. Also information technology materials and Consumer Discretionary have negative coefficients across the board. Sectors that have a overweight of positive coefficients are the Consumer Staples and Health Care. The results suggest that there are some differences in returns among sectors in our sample, but not strong tendencies.

Moreover, we can read from the table how the rating effect varies across sectors by looking at the rgsector variables. One sector stands out from the others, Telecommunication Services, with negative and statistically significant coefficients for the RE and FE model.

Table 15
Regression result including dummies for secotrs

	FM	OLS	BE	RE	RE AR(1)	FE	FE AR(1)
Rating	-.00091*	-.0012***	-.0026**	-.002***	-.0017***	-.00099	-.00085
	(-2.32)	(-4.67)	(-3.11)	(-3.71)	(-5.28)	(-1.05)	(-1.42)
LOG (ME t-2)	-.0013**	-.0018***	.0032***	-.0075***	-.0034***	-.016***	-.016***
	(-2.82)	(-7.84)	(4.28)	(-18.95)	(-12.29)	(-21.70)	(-35.76)
LOG (BTM t-2)	.0011	.0044***	-.0017	.0075***	.0058***	.0078***	.0081***
	(1.44)	(9.41)	(-1.60)	(11.26)	(14.90)	(9.09)	(15.47)
LOG (TO t-2)	.00043	.001**	-.002*	.0011*	.0011**	.0018***	.0018***
	(0.67)	(3.15)	(-1.99)	(2.55)	(3.21)	(3.39)	(4.30)
gsector==Materials	-.000072	-.0026	-.015	-.0095	-.0052	.	
	(-0.02)	(-0.73)	(-1.05)	(-1.13)	(-1.00)	.	
gsector==Industrials	-.0042	-.0045	-.018	-.012+	-.0074+	.	
	(-1.25)	(-1.53)	(-1.53)	(-1.67)	(-1.65)	.	
gsector==Consumer Discretionary	-.00081	-.00019	-.006	-.006	-.002	.	
	(-0.20)	(-0.06)	(-0.49)	(-0.86)	(-0.45)	.	
gsector==Consumer Staples	.0017	.005+	-.028*	.013+	.0072	.	
	(0.46)	(1.65)	(-2.06)	(1.78)	(1.45)	.	
gsector==Health Care	.00094	.0029	-.0068	.014+	.0064	.	
	(0.26)	(0.98)	(-0.52)	(1.93)	(1.30)	.	
gsector==Information Technology	-.0059	-.0019	-.014	-.0049	-.0028	.	
	(-1.57)	(-0.49)	(-0.97)	(-0.57)	(-0.53)	.	
gsector==Telecommunication Services	-.0038	.0026	-.0076	.023*	.0065	.	
	(-0.73)	(0.66)	(-0.47)	(2.41)	(1.05)	.	
gsector==Utilities	-.0072+	-.0098**	-.019	-.015*	-.013**	.	
	(-1.73)	(-3.03)	(-1.34)	(-2.14)	(-2.69)	.	
rgsector==Materials	-.00023	.000075	.0018	.00088	.00033	.0014	.0012
	(-0.46)	(0.19)	(1.52)	(1.09)	(0.73)	(0.94)	(1.45)
rgsector==Industrials	.00028	.00027	.0024*	.001	.00054	.0019	.0019*
	(0.65)	(0.88)	(2.48)	(1.54)	(1.43)	(1.61)	(2.54)
rgsector==Consumer Discretionary	-.00012	-.0002	.00085	.00014	-.00011	-.0002	-.00028
	(-0.26)	(-0.62)	(0.89)	(0.21)	(-0.29)	(-0.18)	(-0.41)
rgsector==Consumer Staples	-.0003	-.00064+	.003**	-.00078	-.00071	.0002	-.000022
	(-0.67)	(-1.89)	(2.69)	(-1.11)	(-1.60)	(0.15)	(-0.02)
rgsector==Health Care	1.8e-06	-.00014	.00087	-.00067	-.00032	.00032	.00022
	(0.00)	(-0.44)	(0.83)	(-0.97)	(-0.76)	(0.25)	(0.25)
rgsector==Information Technology	.0007	.00022	.0015	.00078	.00039	.0018	.0018*
	(1.42)	(0.56)	(1.31)	(0.97)	(0.88)	(1.38)	(2.05)
rgsector==Telecommunication Services	.00032	-.00064	-.00025	-.0021*	-.00089+	-.0036+	-.0038**
	(0.50)	(-1.28)	(-0.21)	(-2.06)	(-1.76)	(-1.76)	(-2.86)
rgsector==Utilities	.00027	.00039	.0017	.0013+	.00079	.0011	.00098
	(0.59)	(1.02)	(1.19)	(1.78)	(1.60)	(0.97)	(1.19)
Constant	.033***	.043***	.0076	.089***	.06***	.14***	.14***
	(4.87)	(11.04)	(0.55)	(11.96)	(11.84)	(20.27)	(30.16)
Observations	295951	295951	295951	295951	295951	295951	292831
R^2	0.147	0.001	0.056			0.010	

t statistics in parentheses
+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Return is the dependent variable. We run Fama-Macbeth, OLS, Between effects, Random effects and Fixed effects with and without autoregressive conditional heteroskedasticity. Fama-MacBeth standard errors are robust to disturbance that is heteroskedastic and autocorrelated using the Newey-West procedure. OLS, BE, RE and FE are robust to disturbance that is heteroskedastic, using Stata's robust option.

Interpreting the results, firms in the Telecommunication Services are more likely to experience lower returns, as credit rating gets worse. Compared to Figure 3 Telecommunication Services is among the sectors with the highest average default rate, but also the highest standard deviation.

The results suggest that there might be some differences across the sectors. However, we must be careful not to draw strong conclusions due to the variation between the models and lack of significant results. Relating again to Figure 3 we recall that the energy sector had medium default rate. Telecommunication Services was third highest, and we observed in our sample that it had a negative and statistically significant coefficient. Utilities on the other hand had the lowest default rate, and have positive coefficients but are not significant. However, we cannot conclude that there are any differences related to the credit rating effect among sectors.

5.2.4 Is the credit rating effect related to the worst rated stocks?

Earlier we showed that there is a negative relation between stock returns and credit rating. In contrast, the results using the portfolio approach suggest that the negative effect is related to the worst rated firms. In this section we search to test if the results are robust by stepwise include one and one rating category into the regression analysis.

Before we go any further Table 16 requires thorough explanation. On the first line, we include only AAA stocks, on the second line we include AAA to AA + on the third line we include AAA to AA and so on, where the last line includes the whole sample as seen in Table 11, from AAA to D. The purpose is to investigate if the credit rating effect is applicable when excluding worse rated stocks.

Table 16
Regression result - stepwise including of one and one rating category

Rating	Rating	LOG (ME t-2)	LOG (BTM t-2)	LOG (TO t-2)	Constant	Observations	R^2
AAA	0	0.00055	-0.012	-0.0069	-0.025	3379	0.513
AA+	0.0041	-0.00053	0.0029	0.0012	0.023	4851	0.496
AA	0.00053	0.00026	0.0021	0.0022	.016*	11769	0.235
AA-	-0.0000095	-0.00023	0.00047	.0031+	.023***	19043	0.16
A+	-0.0003	-0.00023	0.00079	0.0019	.02***	33192	0.104
A	-0.00012	-0.00028	0.001	.0017*	.021***	57847	0.073
A-	-0.00016	-0.00029	0.0011	0.0014	.02***	77454	0.062
BBB+	-.00036+	-0.00051	0.00091	0.0015	.023***	100977	0.054
BBB	-0.00032	-.00056+	0.00099	0.0011	.022***	133494	0.045
BBB-	-0.0004	-.00066+	0.00074	0.0011	.023***	158377	0.062
BB+	-0.00039	-.00082*	0.00063	0.00092	.024***	176411	0.062
BB	-0.00032	-.00087*	0.001	0.00069	.024***	201685	0.062
BB-	-0.00035	-.0012**	0.00062	0.00081	.026***	234174	0.063
B+	-.00047+	-.0012*	0.00051	0.00056	.026***	266455	0.063

B	-.00055+	-.0012*	0.00035	0.00039	.027***	282558	0.063
B-	-.00062+	-.0013*	0.00065	0.00052	.029***	290629	0.064
CCC+	-.00067*	-.0014**	0.0006	0.0005	.03***	293260	0.065
CCC	-.00071*	-.0014**	0.00054	0.00052	.03***	294624	0.065
CCC-	-.00073*	-.0013*	0.00054	0.00049	.03***	295016	0.065
CC	-.00075*	-.0014**	0.00052	0.0005	.031***	295230	0.065
C	-.00076*	-.0014**	0.0005	0.00051	.031***	295244	0.065
D	-.00083*	-.0015**	0.00045	0.00055	.032***	295951	0.065

t statistics in parentheses
+ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$
We run Fama-Macbeth regression. Standard errors are robust to disturbance that is heteroskedastic and autocorrelated using the Newey-West procedure.

Up to AA we observe no negative effect between credit rating and return. The negative effect arises from AA-, but is very modest and statistically insignificant. When we include BBB+ stocks credit rating become statistically significant at the 10 % level with a coefficient of −0.00036. The coefficient does not become statistically significant again until we include B+ rated corporates. Starting with CCC + the effect is around −0.0007 and by including D-rated the credit rating variable, as shown previously, display a coefficient of −0.00083. $LOG(ME_{t-2})$ is statistically significant from the BBB rating. Its magnitude is pretty stable from BB- rated stocks. None of the other control variables are statistically significant at any point.

The results suggest that the credit rating effect is absent among the best-rated firms. Including BBB+ rated firms the coefficient become significant. However, not until we include B+ rated stocks the credit rating effect is significant all the way until D-rated stocks.

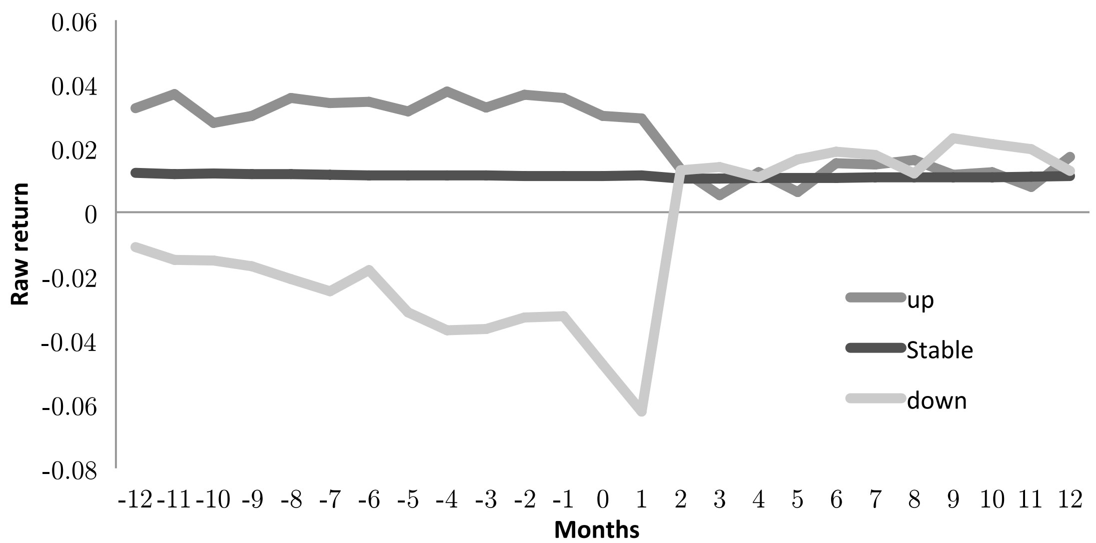
5.3 Returns around downgrades and upgrades

One can expect that in periods when a corporate gets downgraded the returns may be substantially lower than in periods with upgrades. The question is whether the rating agencies add new information to the market, or whether we see a deteriorating (improving) trend in returns ahead of downgrades (upgrades). We will not deduct the direct comparison with an event study, since that could be a separate thesis. We will look at the level of returns, not abnormal returns. The motivation for scratching the surface of this topic is to get an deeper understanding of how investors interprets changes in rating quality, which can contribute to the overall knowledge.

First we show an overview for the full sample in Figure 5 below. The figure show raw returns in percent on the y-axis and the x-axis denote time before and after the event. The time of event takes place at t=0. Arithmetic mean return is calculated 12 months before and 12 months after the event.

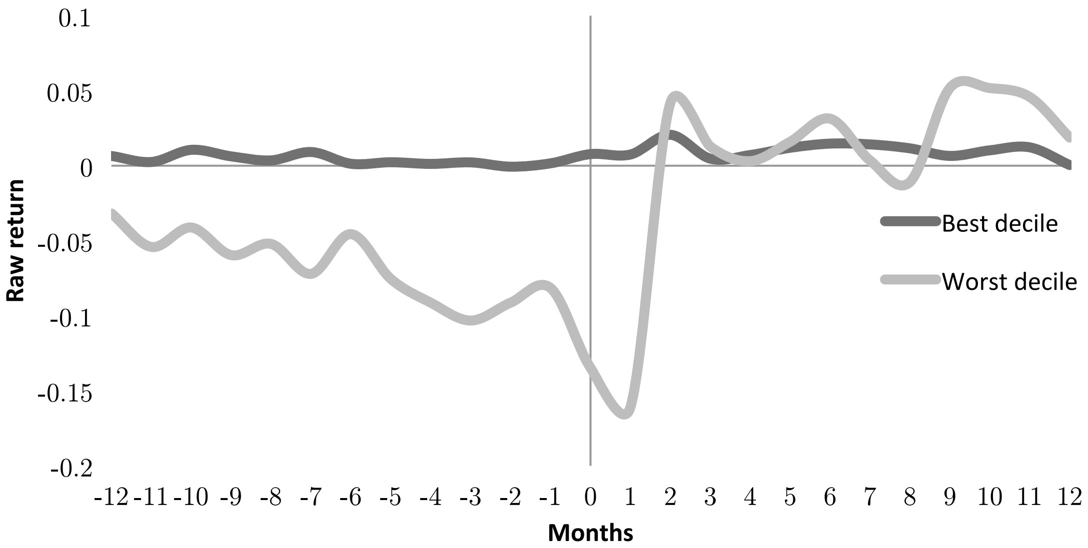
Clearly, we observe that on average when a company gets downgraded the return substantially decreases prior to the event. At the time of downgrade, suddenly the return bounces back to the “stable” stocks. In contrast, around upgrades, returns are higher than the stable stocks and at the time of the upgrade return drop down to the stable stocks after the rating action. If we draw the lines to the previous results, what we observe can indicate reverse causality. Periods with low (high) return may cause the CRAs to react with a downgrade (upgrade) due to a change in financial or non-financial measures. An interesting observation is that return “bounces back” to “stable securities“ after experiencing an upgrade or downgrade. Recalling the economic theory, we may find evidence that around a rating action, investors get compensated for bearing risk in case of a downgrade, and the opposite in case of an upgrade. Another explanation can be that downgrades are more anticipated due to an intensive credit monitoring by bond investors and credit analysts (Finnerty et al., 2010). In addition, CRAs also publishes outlooks and Creditwatch, which can signal a change in rating prior to a downgrade or upgrade. This implies that the downgrade or upgrade may already be priced in the market before a rating action, which can explain the negative (positive) return ex-ante downgrades (upgrades).

Figure 5
Return around upgrades and downgrades



Analyzing downgrades further, we notice a significant difference between the best and worst rated stocks. Using the same portfolios formed in section 5.1, we calculate arithmetic mean return around downgrades 12 months before and 12 months after the downgrade event. The performance of the worse rated securities accounts for huge share of the negative effect as we can observe in Figure 6.

Figure 6
Return around upgrades and downgrades – Best and worst rating decile



Securities in the best decile seem unaffected by the downgrade. One possible explanation is that a downgrade in the worst decile is more crucial than in the best decile. Companies are more likely to be under financial distress and investors may rely more on credit ratings when there is a real danger of a default. We also noticed in Table 10 that the magnitude of an eventually downgrade is bigger in the lower deciles, which can strengthen the negative reaction. However, observing the almost instantly improvement in returns after the downgrade still seem a bit strange and hard to explain.

5.4 Discussion

During the analysis we have shown that there exist a negative relationship between credit rating and stock returns, suggesting that the worst rated companies earn substantially lower returns than better-rated firms. Worse rated firms are also smaller, measured by market value of equity. We show that the credit rating effect is stronger in times of recession than expansion. Among sectors, we cannot conclude with confident that the credit rating effect is different, but we see tendencies that some sectors may be more exposed. The results have passed several robustness-tests, and are in line with previous work, both testing credit rating and other proxies for default risk. It remains now to try to explain why we observe these connections. Lack of theory makes it difficult to draw concrete conclusions, but we will present our thoughts and hypotheses.

CAPM and other risk-return trade-off models suggest that the higher systematic risk the higher return investors can expect. The first obvious thought is that credit rating, or credit risk is not included in systematic risk. According to Dichev (2009) several studies show that a firm distress risk factor could be related to the size and the book-to-market effects. Dichev use bankruptcy as a proxy for firm distress and find that firms with high bankruptcy risk earn lower than average returns. He concludes that book-to-market and size effects are unlikely to be due to a distress factor related to bankruptcy risk. Therefore, it is appropriate that we control for book-to-market and market value of equity in our model. As we observed in Table 9 the beta of the excess return on the market, which is a measure of the exposure to systematic risk, increased as credit quality worsened. We can ask ourselves whether it is the credit rating, other characteristics related to these low rated securities, or a combination that cause this relation between market beta and credit quality. In addition, these low rated, high beta stocks display significant lower returns than the low beta, high rated stocks. In other words, we suggest that there must exist other factors than systematic risk that cause these low returns.

We find in Table 11, running panel data regressions, that credit rating is negative and statistically significant, suggesting that the credit rating effect contribute to explain these lower returns in the low credit quality deciles. The findings suggest that there is a negative relationship between corporate credit ratings and stock returns. We also find a negative relation between size, measured by ME, and stock returns, which is in thread with the existing literature. An important finding in Table 16 and Figure 6 confirms the suspicion that the credit rating effect is related to the worse rated stocks. There is a clear distinction from B+ where the credit rating is negative and significant at the 10% level. Credit risk may be more important when there is a real danger of bankruptcy. The risk-return tradeoff suggests that investors should be compensated for bearing risk, but we observe the opposite when the risk of bankruptcy is significant. In Table 14 we showed that during recession the credit rating effect is stronger, looking at the busr variable. This may also support that credit ratings are more important when financial distress is a reality. Conclusions we can draw for this is that the price of debt is one thing, and default something much more extreme. In the first case the price of debt is reflected in the cost of capital. In the second case of a default, investors are loosing both the return and the equity.

Another explanation can be that the CRAs manage to predict future performance. Thorough analysis of financial and non-financial information, including interviews with management, should provide a good and objective measure of the company's creditworthiness. In contrast to equity ratings, CRAs focus on the downside, and at a longer time horizon (Langhor and Langhor, 2008). It is interesting, that in our sample, the best-rated firms earn on average high returns with low credit risk exposure and a low probability of default. Standard & Poor's underscores that the credit ratings are not buy, sell or hold recommendations, and should be seen in relation to other indicators. Yet, our results suggest that the CRAs manage to figure out which companies that will do well and give them a high rating.

After the financial crisis that occurred in 2007, the CRAs received heavy criticism. The CRAs failed to adjust their rating quickly enough to deteriorating market conditions and underestimated the credit risk associated with structured credit products (Utzig, 2010).

> "..the role of the CRAs goes far beyond elimination information asymmetry. Markets for structured products could not have developed without the quality assurance provided by CRAs to unsophisticated investors about inherently complex financial products. CRAs have operated as trusted gatekeepers" (p. 1).

The ratings of structured products turned out to be less robust predictors of future developments than traditional credit ratings for securities. Without going too much in detail about regulations, which Utzig's paper discuss, we can think about how the market trusted the CRAs opinion about the structured products. Structured products are relatively difficult to understand and determine the associated credit risk. The same goes for companies, and we suppose even large institutional investors consider CRAs opinion in addition to their own analysis. In the extension of this, is it reasonable to believe that the relationship between credit rating and stock returns are partly due to that the market just trusts the CRAs? We cannot answer that question, but it could have been an interesting future topic to research.

6. Conclusions

Analyzing common stocks rated by Standard and Poor's listed on NYSE, AMEX and NASDAQ we find that there is a negative statistically significant relationship between stock return and credit rating. This is a puzzle, because according to financial theories investors will charge a premium for bearing higher risk. Worse rated stocks tend to be smaller measured by market value of equity than better-rated firms. The credit rating effect is also stronger during recessions than expansions, suggesting that when the risk of financial distress becomes a reality the effect is stronger. Among sectors we cannot conclude with confidence that it is differences across sectors, but we see some tendencies. We also find that the credit rating effect is related to the worst rated stocks. The credit rating effect is valid from B+ rated corporates. Seen in relation with the stronger effect during recessions, the effect is also stronger on a firm level when the risk of financial distress becomes a reality.

An interesting observation in our sample is that we observe relatively low market-betas among the best-rated stocks and relatively large market-betas among the worst rated stocks. Following the CAPM, investors demand a higher cost of equity when systematic risk increases. We suggest that it might exist a negative premium when financial distress becomes a reality, due to the potential financial distress costs. A simple explanation to the negative credit rating effect might be that the CRAs manage to find firms that will do well and give them a high rating. Existing literature explains the negative relation with less analyst cover, suggesting that bad news travels slowly (Hong et al., 2000). Kalckreuth (2005) proposes that majority shareholders can extract private benefits from distressed firms, by buying the company's assets or output at low prices. Thus, the observed return is lower than the "real" return for the majority shareholders.

Analyzing downgrades and upgrades we observe that the market participants react to rating actions. However, in Figure 6 we observe that the decline in returns and bounce back effect can be related to the worst rated stocks. The decline in returns prior to the event may be explained by an intensive credit monitoring by bond investors and credit analyst. Also, the possibility that the CRAs publish outlooks prior to an eventually downgrade or upgrade may influence the findings.

Potentially shortcomings may be several. First of all, reverse causality can be a reason why we find what we find. It may be a possibility that credit ratings follow returns, and not returns follow credit ratings. Consequently, it is possible that it is too easy to reject the null and conclude that the negative effect exists. It may be that the market is not puzzling, but it is hard to estimate the behavior due to causality potentially running in both directions. The reverse causality we observe can be due to credit rating outlook and CreditWatch. If a corporate receives a negative outlook for instance, 10 months before it gets downgraded, we should expect the information to already be reflected in the stock price. This may also contribute to explain why we observe the negative returns prior to downgrades.

In the extension of this study it could have been interesting to investigate if there is consistency between the credit ratings provided by Standard & Poor's, Moody's, and Fitch. Some firms are rated by multiple CRAs, and it would be interesting to see if there are any differences on how the market perceives the different credit ratings.

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Appendix

Apendix 1 – Variable description

Variable	Description	Units	Source
RET	*Adjusted holding period return, adjusted for DLRET.*	Percentage	CRSP
DLRET	*The return of the security after it is delisted. It is calculated by comparing a value after delisting against the price on the security's last trading date*	Percentage	CRSP
Shrout	*Shares outstanding*	Millions	CRSP
Price	*Price at end of months*		CRSP
Vol nyse/amex	*Monthly trading volume, rounded to the nearest hundred*	Hundred shares	CRSP
Vol nasdaq	*Monthly trading volume,*	Hundred shares	CRSP
Credit Rating	*S&P Domestic Long-Term Issuer Credit Rating*	AAA-D	Compustat/NA/Ratings
ATQ	*Assets - Total*	Millions	Compustat/NA/Fundamentals Quarterly
LTQ	*Liabilities - Total*	Millions	Compustat/NA/Fundamentals Quarterly
bus	*Business cycles according to NBER. It takes value 0 if expansion and value 1 if recession*	Dummy	NBER
busr	*BUS multiplied with RATING*	Dummy	
Turnover	*Share volume divided by the total number of shares outstanding*	Percentage	CRSP
ME	*Market-value of equity*	Millions	CRSP
BTM	*Book-to-market ratio*		CRSP and Compustat
Event	*Takes 0 if downgrade, 1 if nothing 2 if upgrade*	Dummy	
gsector	*Dummy for each sector*	Dummy	
rgsector	*gsector multiplied with rating*	Dummy	

Appendix 2 – Standard and Poors Rating Categories

This table shows how Standard and Poor's describe the long term issuer credit ratings categories. The description is gathered from http://img.en25.com/Web/StandardandPoors/SP˙CreditRatingsGuide.pdf

'AAA'	Highest rating. Extremely strong capacity to meet financial commitments.	Investment Grade
'AA'	Very strong capacity to meet financial commitments	
'A'	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances	
'BBB'	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions	
'BBB-'	Considered lowest investment grade by market participants	
'BB+'	Considered highest speculative grade by market participants	Speculative Grade
'BB'	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions	
'B'	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments	
'CCC'	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet	
'CC'	Currently highly vulnerable	
'C'	A bankruptcy petition has been filed or similar action taken, but payments of financial commitments are continued	
'D'	Payments default on financial commitments	
Ratings from 'AA' to 'CCC' may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the major rating categories.		

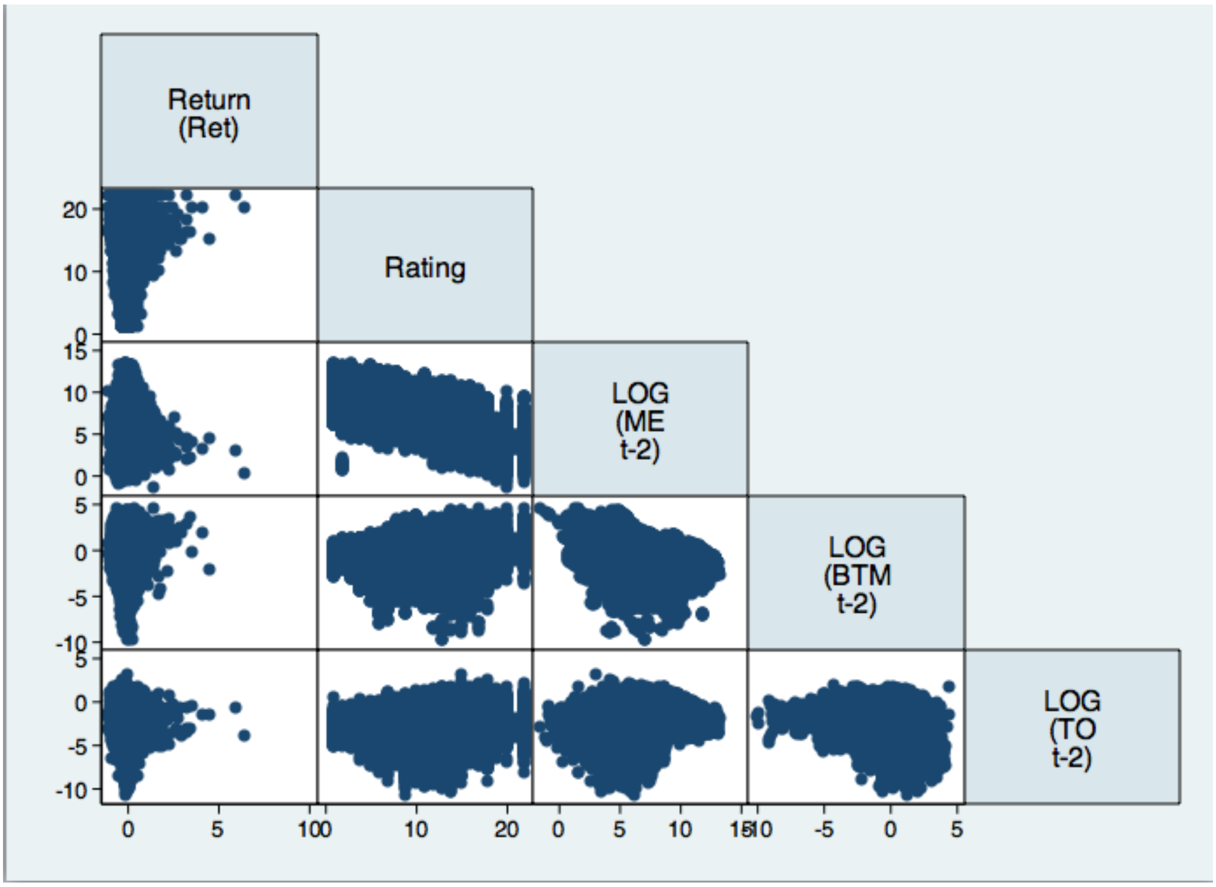
Appendix 3 – Econometrical diagnosis[4]

The purpose of this appendix is to describe the data sample in more detail. We show figures and test results from Stata, examining outliers and influential data, normality, homoscedasticity of residuals and multicollinearity.

Outliers

Figure 7 show a scatterplot matrix of return, credit rating, LOG (ME_{t-2}), LOG (BTM_{t-2}) and LOG (TO_{t-2}). We especially notice some return outliers among the worst rated stocks (and smallest stocks).

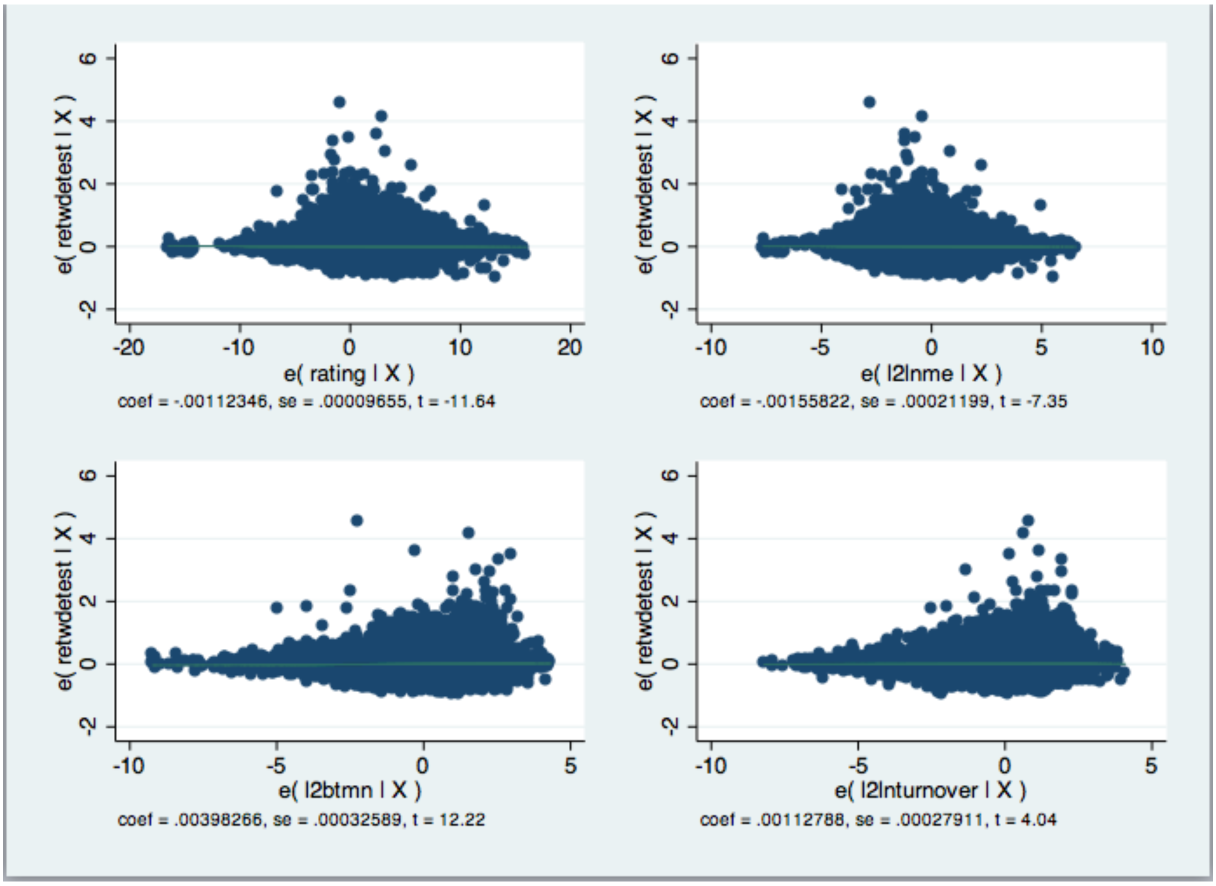
Figure 7
Scatterplots



[4] The following analysis is motivated by http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter2/statareg2.htm

Figure 8 graphs a partial-regression plot, which is useful to identifying influential points. It is based on OLS regression. We notice some points that may have influence our results.

Figure 8
Added variable plot



Homosecadisticity of residuals

Assumption 5 in the CLM assumes the error terms equal variance (homoscedasticity). In Figure 9 we plot the residuals versus fitted values. If the variance of the residuals is non-constant we say that the residual variance is heteroskedastic. We clearly see that the data points in the left end are much narrower than in the right end. This indicates heteroskedasticity. We can also apply statistical tests, which test if the residual variance is homoscedastic. According to the Breusch-Pagan test in Figure 10, we must reject H0 and accept that we have considerable signs of heteroskedasticity in our data sample. Hence we must apply robust standard errors.

Figure 9
Residuals versus fitted (predicted) values

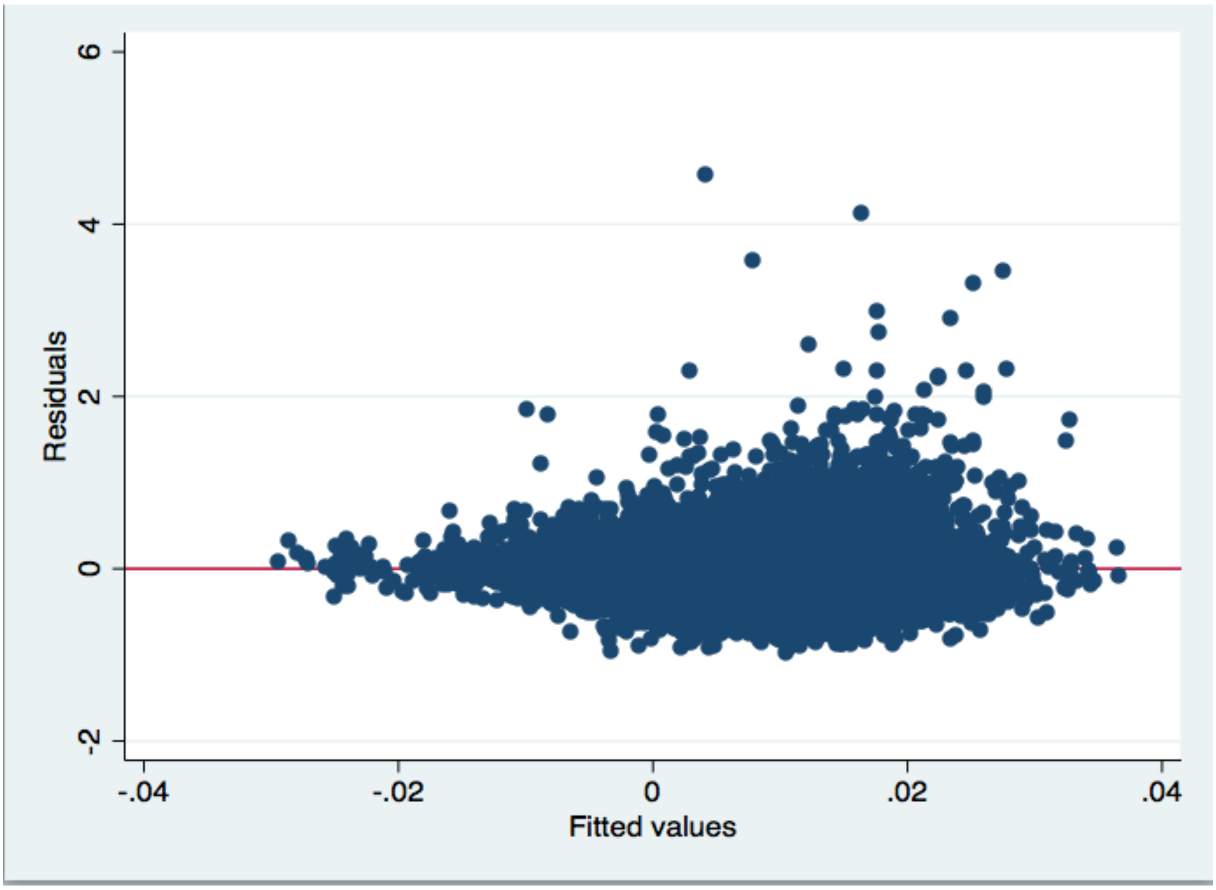


Figure 10
Breush-Pagan test for heteroskedasticity

Ho: Constant variance

chi2(1) = 762.24
Prob > chi2 = 0.0000