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Does increased creditworthiness lead to a reduced interest rate?

A study of external credit ratings' potential to influence a company's average interest rate

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Summary

The main objective is to explain whether increased creditworthiness leads to decreased average interest rates. The creditworthiness is represented by Bisnode's credit rating codes. Involved in the study are Norwegian limited liability companies. The assessment extends from 2005 to 2011, and the analyses were executed for each year separately. The motivation has been to verify if creditors are covering credit risk responsibly by requiring an amount of compensation, in the form of an interest rate, which is at par with the perceived level of company credit risk.

The credit rating codes are divided into five categories and regression analysis has been applied in order to detect whether the differences between the interest rate per credit rating code are statistically and economically significant.

Almost all interest rate differences between the credit rating codes are found statistically significant. The findings do not apply to the interest rate difference between AAA- and AA-rated companies or between AA- and A-rated companies, due to insignificant results. The order of the differences is as expected. C-rated companies carry higher interest rates than B-rated companies, which carry higher interest rates than A-rated companies, etc. The economic significance is considered high due to the large size of the interest rate differences and because credit rating code changes are detected frequently. This proves that firms extending credit rating codes contribute to enable well-functioning credit markets between debtor and creditor on the capital market.

One of the limitations of this thesis has been the aggregated level of the interest rates. When executing further research, it would be advantageous to access less aggregated data and also to increase the sample size. In to obtain more accurate average interest rate calculations, the interest rates should be weighed according to the size of the relevant firm's interest-bearing debt.

Preface

This thesis has been written as the final study related to the master program at the Norwegian School of Economics.

The chosen topic came to life after several rounds of discussions with supervisor Øyvind Helgesen as well as with other professors at school. It especially started to take shape when I was made aware of the data set available for analysis. In the light of recent financial distress, it is important to increase the awareness of detecting as well as covering credit risk. On the subject, credit rating codes are useful indicators of credit risk.

This process has not only increased my knowledge on the topic of credit risk evaluation, but it has taught me the process of employing and analyzing data and deriving statistical results.

I would like to thank my supervisor, Øyvind Helgesen, for frequent feedback steering me in the right direction and for his efforts to transfer professional insight which has expanded my perspective on the chosen topic.

Also, many thanks are directed towards Aksel Mjøs, Arnt Hopland, Kjell Henry Knivsflå and Eylert Brodtkorb.

Last, but not least, I would like to thank Bjørn Are Aamnes Mostue for his continuous support.

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Kaja Marie Brodtkorb

Abbreviations

CEO	Chief Executive Officer
CRAs	Credit Rating Agencies
EAD	Exposure at default
ECA	Export Credit Agencies
EL	Expected loss
Fitch	Fitch Ratings
GIEK	Guarantee Institute for Export Credits (The Norwegian ECA)
IFRS	International Financial Reporting Standards
LGD	Loss given default
Moody’s	Moody’s Investors Service
Nibor	The Norwegian InterBank Offered Rate
NHH	The Norwegian School of Economics
NRSRO	Nationally Recognized Statistical Rating Organizations
OLS	Ordinary least squares
PD	Probability of default
SNF	The Centre for Applied Research at the Norwegian School of Economics
S&P	Standard and Poor’s Rating Services
The big three	Moody’s, S&P and Fitch

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Introduction

1.1 The importance of credit ratings

Credit ratings are widely recognized measures of relative credit risk (S&P, 2011). They are applied on people, entities and single debt instruments as well as on sovereigns. Employers of such information may be both (potential) employees, customers, suppliers, credit extenders, auditors and the public (Gjesdal, 1980). This paper focuses on *companies* as credit rating objects and how their received credit rating codes may affect their average cost of capital. More specifically, the focal point is the credit rating's effect on the cost of debt, i.e. the effect on the average interest rate.

When a company is in the market for credit, its creditworthiness is evaluated. The evaluator could be the counterparty himself or an external agency. "Creditworthiness risk is the uncertainty surrounding a firm's ability to service its debts and obligations" (Benhayoun, Chairi, El Gonnouni, & Lyhyaoui, 2013, p. 105). Receiving a relatively favorable credit rating code signalizes low credit risk and thus a relatively smaller probability of company default. Consequently, the credit extender may require a lower interest rate and the company with the favorable rating code reduces its cost of debt. The *number* of players willing to extend credit to the company may also increase, leading to an increased ability to access cheap capital, perform competitive business and to stay in the market as a worthy participant.

Credit rating codes may also contribute to facilitate more efficient decision making. Entities entering into contracts containing credit deals may encounter problems regarding adverse selection and moral hazard. The borrower has more knowledge of his own creditworthiness than the lender has, and this may lead to information asymmetry (Skarsvåg, 2005). However, credit rating agencies, CRAs, are said to be "financial intermediaries between borrowers and lenders" (Shahzad, 2013, p. 2). Information asymmetry and information costs can be reduced, thus facilitating trust and making the market more efficient and transparent (Taylor, 2013). This enables companies and governments to raise money in the capital markets. Credit rating codes even play a regulatory role in conjunction with investment restrictions and regarding the calculation of banks' minimum capital requirement.

Credit rating codes have the power to influence financial decision making. Consequently it is of interest to gain more knowledge on the topic, leading to the introduction of the research question.

1.2 The research question

This thesis investigates the relationship between a company's creditworthiness and the interest rate. The research question reads as follows:

Does increased creditworthiness lead to a reduced interest rate?

The hypothesis is that there is an inverse relationship between the creditworthiness, represented by the credit rating codes, and the interest rate, and that this relationship is statistically significant[1]. In order to pave the way for the research question, underlying issues such as *what is creditworthiness* and *what is an interest rate*, emerge. The purpose of this paper is to answer the principal research question and to verify the hypothesis. The economic consequences of these findings are also addressed.

1.3 The foundation

In order to answer the research question, an accounting database collected by the Norwegian School of Economics, NHH, and the Centre for Applied Research at the Norwegian School of Economics, SNF, is applied. Having this data base at hand enables the study of the relationship between the creditworthiness, communicated through credit rating codes, and the interest rate, also applying control variables. The relationship between these variables is portrayed in figure 1.1, and further developed throughout this paper. An expanded illustration is presented after all relevant variables have been described.

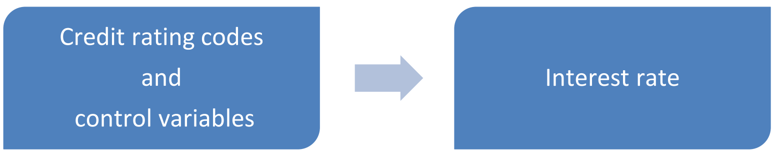

Figure 1.1 The foundation

[1] When applying the word *significance* in this thesis, it refers to statistical significance if not otherwise stated.

1.4 The structure

This thesis begins with a theoretical framework, constituting its backbone. Firstly the dependent and the independent variables in the study are addressed. Secondly, the demand and supply for credit rating codes are laid out through a sub-section referring to credit rating players. Thereafter follows a segment explaining credit rating calculation methods and how they are communicated through coding schemes. Lastly, potential control variables and the hypothesis of this thesis are elaborated upon. Succeeding the theoretical framework, information on the data set and methods applied follows. In the fourth section, the results are documented and in the fifth they are discussed. Implications are also conferred in section five, including suggestions for further research. The conclusion completes the thesis.

On the next page follows a model of the structure.

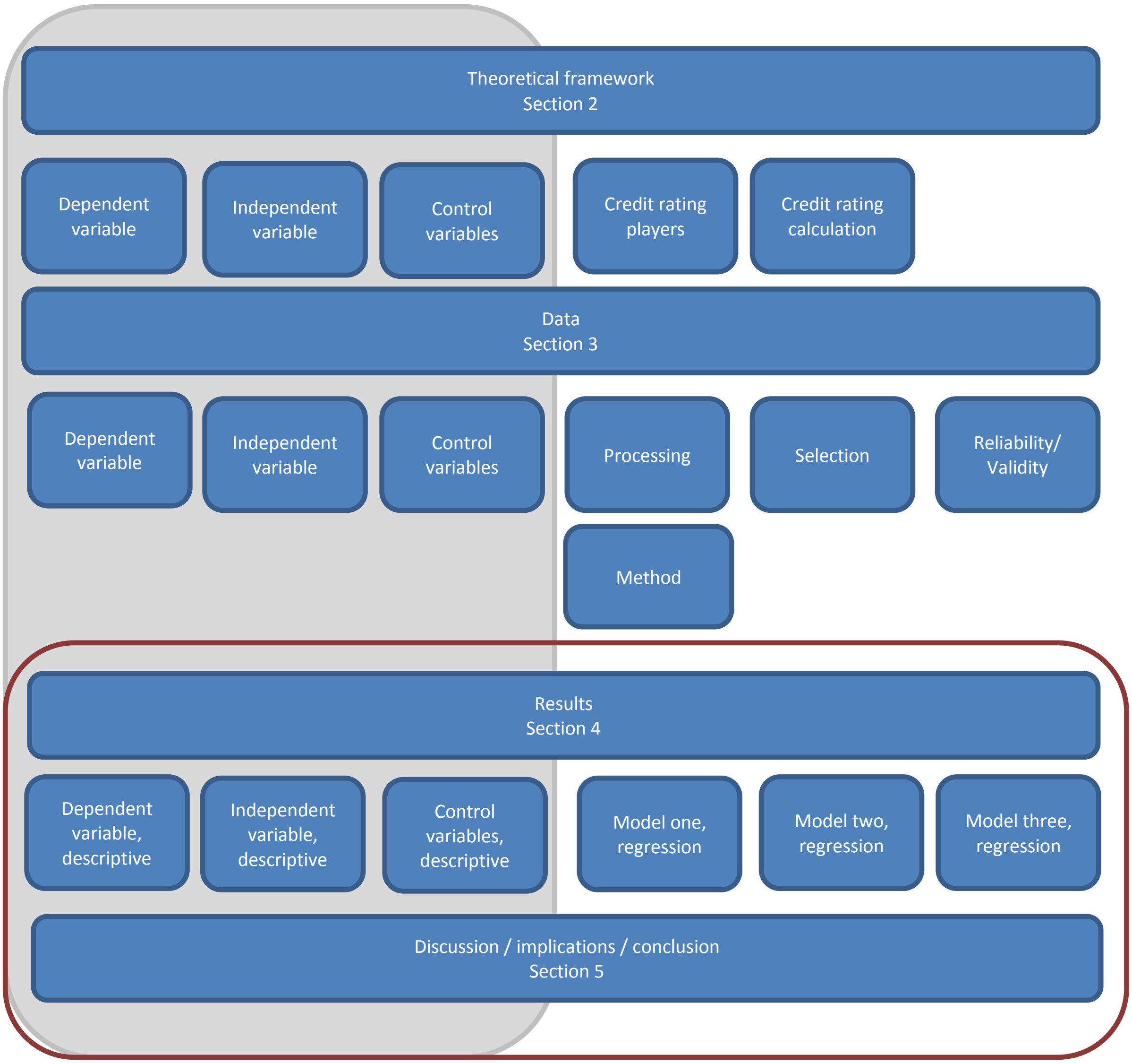

Figure1.2 The structure of the thesis

The left grey area in figure 1.2 shows a continuous focus on the dependent and independent variables as well as the control variables. The additional areas covered are illustrated on the right, supporting the analysis of the relationship between the variables on the left, leading to the findings in this study, which are circled.

2. Theoretical framework

As illustrated in figure 1.1, the major parameters applied in order to either reject or ratify the research question in this thesis are the average[2] interest rate, the credit rating codes and the control variables. Theoretical framework on these variables is presented below.

2.1 The dependent variable, the interest rate

A rate of interest may be defined as “the per cent of premium paid on money” (Fischer, 1930, pp. 13-14). Even though this was written in 1930, it still applies. The premium is calculated based on money traded between present and future. This money is also called credit. Credit can take different forms, have different maturities, be retrieved for different reasons, originate from different sources and carry different amounts of credit risk. All these factors influence the size of the interest rate.

The reporting of multiple types of credit following below is not all-encompassing as this is not the purpose. The purpose is to make the reader aware of the vast amount of sources of credit, i.e. sources of interest rate, which exist. This understanding is beneficial for further reading.

There are many ways to categorize credit. One may, for example, apply characteristics describing durance or purpose or divide between credit that bears interests and those that do not. The following breakdown distinguishes between purposes, i.e. company needs, and also mentions the credit’s link to durance.

Firstly, companies may need credit in order to finance daily operations. These credits are of a more short-termed character. Secondly, companies need credit for larger investments in non-current assets, often more long-termed. Examples of the former type of credit are accounts receivables and inventory. These are called current assets. Costs may also arrive sooner than the income, thus obliging companies to obtain credit. This especially concerns companies influenced by seasonal changes. Various expenses connected to current assets may be covered by credit lines, confirming, market financing, factoring or by promissory

[2] Occasionally, the “average” is referred to as the “mean”.

notes. These are short-term financial solutions. A line of credit is used by companies in order to withstand short-term liquidity fluctuations. The interest rate paid is often a combination of the interests on the amount used and on the given credit limit. The second short-term debt mentioned, confirming, defines credit obtained to cover inventory (Kronborg & Thoresen, 1985). Market financing describes two players interacting on the market, with or without a broker, borrowing money from each other. The interest rate paid is often higher than what a creditor could achieve by putting the money in the bank or purchasing bonds (Banken & Busch, 1986). In this thesis, a creditor refers to the “one to whom a debt is owed” (Encyclopaedia Britannica, 2014), whether this creditor is a financial institution or any other company issuing credit for a fee. Factoring is when one company, the “factoring company”, purchases another company’s accounts receivables. Promissory notes simply describe when credit is issued in exchange for interest rate and principals.

Non-current assets are, for example, real estate, machines and transport. For these purposes, longer-term loans, and often larger loans, are necessary. Commercial banks, savings banks, pension funds as well as life insurance and general insurance companies are possible creditors. In the banking industry in Norway, 67 per cent of business loans are offered by commercial banks, 23 per cent from savings banks, six per cent from credit institutions and four per cent from others. The limited liability companies represent 91 per cent of the demand toward loans from these financial institutions (Mjøs & Phan, 2011).

In order to meet the demand for long-term credit, banks issue several products. Among other products, they include mortgage loans, construction loans, promissory notes, bonds, convertible loans and leasing. For (commercial) real estate, mortgage loans are frequently applied, taking security in the estate. Construction loans have similar characteristics as credit lines. The debtor pays provisions on the credit limit agreed upon as well as interests on the credit which is drawn (Kronborg & Thoresen, 1985). In addition to banks, bond issuers also comprise states, municipalities and other large limited liability companies. Bonds are loans divided into parts where both individuals, companies, banks and others may buy one or more bonds (Lederkilden). If a creditor needs the money back, the bond may be sold on a secondary market (Kronborg & Thoresen, 1985). Regarding bonds, the *credit spread* is often mentioned. This is the “positive yield spread over a comparable-maturity Treasury bond” (Ng & Phelps, 2011, p. 63). The spread compensates investors for investing in risk-containing securities with a greater default probability than a treasury bond. An investor is one who “commits (money) in order to earn a financial return” (Encyclopaedia Britannica, 2014). As the level of the risk free rate may be different in different countries and changes depend on the relevant maturity, the spread is of greater interest than the absolute level of the interest rate (Nilsen, 2005). Bonds are often applied when companies need to borrow large amounts of money. Convertible loans are bonds that can be converted into stocks. The choice made depends on the market value of the stocks and the nominal amount of the bond (Berner, Mjøs, & Olving, 2013). When one party pays another party for the right to use fixed assets for a specific time period, this is called leasing. This financing solution is applied in order to free up capital for other investments.

It has not been mentioned, but some products mentioned as either long- or short-termed may also be medium-termed, depending on the needs of the company as well as on negotiation terms.

All products mentioned above carry a cost, often referred to as an interest cost. The relative cost of long-term debt is often more expensive than short-term debt. The risk increases as the debtor has more time to default. The average interest cost in a company is a fusion of interest costs belonging to their respective liabilities, posted on the balance sheet. Some debt categories are considered non-interest-bearing, for example payables to suppliers. However, these suppliers know that they will not get paid until later and thus calculate an additional fee *into* the price of their products/services (Bergstrand, 2009). This additional fee is disregarded in the calculation of a company's average interest rate as the amount is unknown. If a company defaults on a payment of interest costs, provision or principal, the creditor can demand a *default* interest, also called a *penalty* interest. In Norway, the government regulates the level of this interest rate through the "Late Payments Act". The rate follows the Key Policy Rate adding at least eight per cent on top of it (The Financial Supervisory Authority of Norway, 2013).

The size of the interest rate depends partly on the degree of risk aversion held by the creditor. The higher the risk, the higher the interest rate demands (Sættem, 2006). Risk is divided into several categories. One of them is credit risk, evaluated either by the creditor or an external agency. More information regarding credit risk follows in section 2.2 to 2.5. Short-term bank loans often have a fixed interest rate, whereas the interest rate on longer-termed bank loans is often linked to a common benchmark (Brealey, Myers, & Marcus, 2012). This benchmark could, for example, be the Norwegian Interbank Offered Rate, nibor. This rate is the money market rate in Norway and it is the interest rate that banks pay to borrow money from each other. This affects the interest rate level that the banks can offer their customers. If the nibor is high, so will the interest rates they require from their customers most likely be.

An interest cost is entered into a company's income statement as an expense. Paying back principals, on the other hand, is not an expense, and reduces the total capital in the balance sheet (Sættem, 2006). The average interest rate applied in this specific report is further explained in section 3.5.1.

2.2 The independent variable, the credit rating codes

A credit rating is described by the European Union as "an opinion issued by a specialized firm on the *creditworthiness* of an entity (e.g. an issuer of bonds) or a debt instrument (e.g. bonds or asset-backed securities)" (European Commision, 2013). Credit ratings are futuristic and therefore subjective by nature (hence "opinion"). The quantification of the analysis contributes to make it more objective. As there are a *vast* and *diverse* number of factors involved in the credit ratings of various targets, all credit rating cannot be realized using *one* common method. This is underpinned in the sub-section regarding credit rating calculation. External credit ratings are welcomed by companies, as calculating them is very time-consuming and requires specialized knowledge to perform (de Haan & Amtenbrink, 2011).

2.2.1 Creditworthiness

As the word creditworthiness indicates, it is about being "worthy of credit" or not. Being labeled "worthy of credit" sends a signal that an entity can be trusted to pay back the credit. This eases the entity's access to capital and may also positively affect the size of the interest rate. The latter inference is the one under investigation in this paper. When trying to predict a company's ability to handle its debts in the *future*, historical payment alone behavior is not sufficient to analyze a company's creditworthiness. Creditworthiness is "a forward-looking concept, focusing on the probable incidence of credit difficulties in the future" (Fiedler, 1971, s. 10). These "difficulties" can be represented by measures of the probability of default. The probability of default is a frequently used term depicting creditworthiness. When the probability decreases, it is more likely that the credit is paid back in full. The creditworthiness, represented by the calculation of probabilities of default, is presented to the public using credit rating *codes*.

2.2.2 A short timeline of credit rating

In 1859 the first creditworthiness guide was published by Robert Dun. John Moody founded the first CRA 50 years later. In 1916, Fitch Ratings was founded and in 1941 Standard Statistics and Poor merged to become Standard & Poor's (Langohr & Langohr, 2008). In 1936, bank regulations in the United States began requiring banks only to invest in bonds receiving a rating above "investment grade" from at least two agencies (Adams, Mathieson, Schinasi, & Chadha, 1998). Having an investment grade means obtaining one of the best evaluations, further elaborated upon in section 2.4.1. This led to imbedding the CRAs' work into the United State law, giving them increased power to influence the market (White, 2007). From 1970 to 2001, the global financial system became market-based and the demand for CRAs increased (Langohr & Langohr, 2008). Today, however, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 is reducing the overreliance on CRAs, scaling down the references to external CRAs in regulations (European Commision, 2013). This is also occurring in the European Union where banks are encouraged to use *internal* models when measuring risk. Issuers of structured finance instruments are also demanded to be more transparent regarding the underlying assets and issuers are required to engage two CRAs to rate structured finance instruments and to switch CRA every four years (European Commision, 2013).

Even though criticized for undermining credit risk during the financial crisis, and the attempt to reduce the overreliance, the dependency on CRAs does not seem to be expiring any time soon. The demand for transparency, however, has increased.

2.3 Credit rating players

A credit rating may be *official* or *unofficial*. An official rating is publicly available, paid by the issuer[3] and extended by one of the recognized CRAs (Alessi, Wolverson, & Sergie, 2013). Unofficial rating codes can be created by any other player in the credit evaluation business.

[3] The relevant issuer here is the issuer of the instrument, i.e. the debtor seeking credit.

The categories of credit information extenders are not undisputable competitors. They answer to different demands. Which agency a player should contact partly depends on the credit guidelines of the player. Perhaps there are demands regarding the application of certain CRAs. If international capital is required, and often when large amounts of capital are needed, the players turn to the large CRAs. As the service of the largest CRAs is very expensive, it also requires a certain size before a company can afford it and can receive the benefits from it. The country of origin of the counterparty also matters. Does the counterparty originate from the same country; a smaller national credit information extender may suffice.

2.3.1 Credit Rating Agencies

Moody’s Investors Service, Standard and Poor’s and Fitch Ratings are called the *big three* CRAs. From now on, these are called Moody’s, S&P and Fitch, respectively. Together they have a market share of 95 per cent of the world market (European Commision, 2013). Even so, there are an additional seven Nationally Recognized Statistical Rating Organizations, NRSRO, in the United States (SEC, 2014 a). In the European Union, 24 CRAs are certified (ESMA, 2014). Lists can be found in the appendix as attachment 7.1 and 7.2. When referring to CRAs, the focus consistently remains on the big three.

In 2011, Moody’s mostly rated issuers of government securities, constituting 81.5 per cent of their total rating activity. 9.4 per cent of the rating information was purchased by issuers of asset backed securities, 5.7 per cent by financial institutions, 3.0 per cent by corporate issuers and 0.4 per cent by insurance companies (White, 2013). These are defined as Moody’s customers. The typical bond holders, i.e. firms turning to CRAs for credit risk information, are thus not households, but institutions (White, 2013).

Prior to the 1970s, *investors* paid CRAs to access information on issuers. Today, the issuer-pays-model is predominant (Alessi, Wolverson, & Sergie, 2013), after S&P started the trend in 1974 (S&P a)[4]. Creditors rely on the CRAs’ analysis as it may be their main source of information regarding the level of risk in potential investments. This issuer-pays model has been exposed to critique, as it may lead to a conflict of interest. The issuer might “shop around” to search for the agency giving the highest rating code. For this reason, the

[4] Again, the issuer refers to the debtor.

independency of CRAs might be questioned. However, White (2013) suggested two reasons for the change in the payer's model from investor-paid to issuer-paid. The first one was the increasing possibility of photocopying of information. The second one was that it became clear, due to the increased use of CRAs in regulations, that their services were truly needed. An additional reason encouraging the model change was that the issuers' threat of going elsewhere unless receiving a good rating code was not strong enough. A rating agency can namely issue an unsolicited rating code. This means that the agency does not receive any remuneration for it. The CRAs can thus indirectly threaten to issue a "bad" unsolicited rating unless paid for it. CRAs may also issue unsolicited ratings in order to cover a certain market or perhaps access a new market (Financial Times Lexicon).

Sovereigns also seek to be rated by external CRAs in order to ease the access to global capital markets (Langohr & Langohr, 2008). For example, Norway's long-term issuer default rating is top rated by all the big three (solicited by S&P and Moody's), enabling Norway to access cheap capital on the international capital market.

Furthermore, CRAs issue *country ceilings*. According to Fitch, country ceilings are not ratings, but expressions of the "maximum limit for the foreign currency issuer ratings of most, but not all, issuers in a given country" (Fitch).

2.3.2 Business information providers

Business information providers gather company data from many different sources and offer a vast amount of services based on this information. Sources may be various registers, such as the Register of Business Enterprises, the Register of Mortgaged Movable Property, the Register of Company Accounts as well as Debt Collection Agencies (Skarsvåg, 2005) and the companies themselves. The customers of business information providers have different needs and purchase different services. They can choose to access raw accounting data, unofficial rating information *or* purchase credit management solutions to integrate in their own internal systems.

The largest suppliers of business information in Norway are Experian and Bisnode. Experian is the leading global information services company (Experian, 2014)**.** It is listed on the London Stock Exchange and is present in 40 countries. One of their global business lines is *credit services*, analyzing credit risk assisted by their 13 credit bureaus (Experian a). Bisnode is present in 19 European countries (Bisnode). In Norway, Bisnode is divided into five companies and one of them is Bisnode Dun & Bradstreet, distributing the rating codes applied later in this paper.

In contrast to the issuer-pays model of CRAs, the investor-pays model is the predominant model when considering business information providers. According to the Discipline Manager in the credit department at Bisnode, Per Einar Ruud, there is one exception. Companies competing to win contracts pay for and submit their own credit rating codes (issuer-pays model).

Business information providers are important players on the national market, especially for smaller institutions lacking the resources to rate customers themselves. Roughly speaking, all players issuing credit are potential customers of business information providers. In order to enable a quick response to credit risk changes of their debtor(s), the creditors need not only to check customers' creditworthiness, but to monitor their behavior over time. Examples of customers are telecom companies, insurance companies, real estate companies and the retail sector. However, the largest demand derives from banks. They buy raw data and add this to their own data obtained directly from their customers before calculating *internal* rating codes.

2.3.3 Banks

Banks, insurance companies, finance companies and investment companies are able to analyze customers themselves as they are lending experts (White, 2013) and as the sources of information are easily accessible. The banks' procedures are explicitly described below, as regulations require them to rate customers in a particular way.

Banks are especially interested in credit rating codes not only because their *core* business is built on evaluating (potential) counterparty creditworthiness, but because regulators accept rating codes as elements of calculating the minimum capital requirement. Banks are heavily regulated in order to create trust in the market. The Basel Committee on Banking Supervision is a global committee that "establishes minimum standards for the prudential regulation and supervision of banks" (BIS). The representatives are members of central banks and banking supervisions and are all voluntary members. The Basel Accords are agreed upon by the member states and have no legal force. Nevertheless, it is expected that they are implemented by the individual national authorities. The Basel Accords communicate how much *regulatory capital* a bank must have at all times in order to cover its risks in a responsible manner. The Basel Committee's recommendations are usually followed up by the European Union Directives and are also, due to the European Economic Area Agreement, implemented as Norwegian regulations (The Financial Supervisory Authority of Norway, 2010).

The Basel accords are built on three pillars. Pillar one presents the minimum capital requirement (*The Solvency Ratio)* and how to calculate it. It must be at least eight per cent of risk weighted assets. The risk weights are based on the probability of default.

The second pillar of the Basel Accord is the *Internal Control and Supervisory Review*. This pillar is about evaluating the appropriateness of the models applied in conjunction with pillar one. The evaluation process is called The Internal Capital Adequacy Assessment Process. Risks not taken into consideration through pillar one should be reviewed here, as well as the risk in conjunction with the impreciseness of the models (The Financial Supervisory Authority of Norway, 2009a).

The third pillar is *market discipline* and has implications for disclosure requirements. Reports on models and the implementation of Basel II (the current version of the Basel Accords) must be produced and disclosed. This puts pressure on banks to enhance risk management procedures and enables external players to understand their rating procedures. Information regarding the calculation of credit rating codes in banks is found in section 2.5.

Today, Basel III is increasing the capital requirement and, according to the Chief Financial Officer in Fana Sparebank, Kim Lingjærde, obliging banks to invest in a larger amount of covered bonds. A covered bond is "a bond which gives investors recourse to a specified pool of the issuer's assets" (Bakke, Rakkestad, & Dahl, 2010, p. 4). In order to issue covered bonds, the issuer has to obtain an *official* rating code, making it even more favorable *and* necessary to be rated by one of the recognized CRAs (Bakke, Rakkestad, & Dahl, 2010).

2.3.4 Export Credit Agencies

An Export Credit Agency, ECA, is often a governmental institution. The goal of an ECA is to support its own country's exports. The ECA in Norway is called the *Guarantee Institute for Export Credits, GIEK,* and is a public enterprise under the Ministry of Trade, Industry and Fisheries. GIEK guarantees government-backed loans given to international companies wanting to do business with Norwegian exporters (with a specific focus on developing countries and emerging markets). Before setting the price for such a service, GIEK collects credit information from business information providers and performs credit assessments using a risk assessment model. The interest rate depends on risk, bank participation and the possibility of security (GIEK, 2013). The members of the Organization for Economic Co-operation and Development have a *gentlemen's agreement* expressing minimum interest rates, in order to reduce extreme price competition (OECD)[5].

2.3.5 Brokerage houses

On the international bond market, the bond issuer needs to obtain an *official* rating code. On a national level, however, not all players obtain rating codes from the big three. Brokerage houses are then available to analyze the credit risk, issue *unofficial* rating codes and play the role as *broker* between a national bond issuer and potential national investor. Examples of such brokerage houses in Norway are DnB Markets and Nordea Markets. Through applying credit rating codes in their evaluations, they facilitate an efficient bond market, matching buyer and seller in terms of conditions. These players contribute with decisive information when the creditor is calculating the appropriate interest rate.

2.3.6 Factoring companies

Factoring companies are specialized firms acquiring the responsibility for other companies' accounts receivables. Their customers are from now on called clients. The accounts receivables are bought by the factoring company for an amount below face value in exchange for a fee. Factoring includes checking the credit risk of the accounts receivables, i.e. the client's *customer's* creditworthiness. The providers of factoring services become experts on evaluating accounts receivables. Players engaging factoring companies are those needing to raise capital quickly, as the factoring company advances cash to pay for the receivables. Factoring may also be purchased by those that do not have the resources to handle their accounts receivables in a correct and timely manner themselves (Soufani, 2001).

[5] This is simply an example of the application of credit ratings. The interest rate referred to is paid by foreign companies and is thus not a part of the average interest rate of the *Norwegian* companies involved in this study.

2.4 Credit rating calculation

Exactly *how* a credit rating code is calculated is often a “company secret”. In the United States, The Securities and Exchange Commission, SEC, *oversees* the NRSROs, but is not allowed to *regulate* their rating methodologies. However, through the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, *disclosure requirements* of credit rating methodologies and assumptions were introduced (SEC, 2014 b). This Act makes it easier to understand rating codes, without forcing CRAs to reveal their entire internal processes. The same development has been encountered in Europe through the European Securities and Markets Authority, ESMA, the regulator of CRAs in the European Union.

A credit rating may be executed on a company, on an instrument or on a country. The focus in this thesis is on company ratings. A general credit rating analysis may look like the one presented in figure 2.1, starting to the left, continuing towards the right.

Figure 2.1 Credit rating analysis

Source: (Langohr & Langohr, 2008)

According to Langohr and Langohr (2008), a credit rating is based on an analysis of both business risk and financial risk. Business risk is influenced by company risk and industry risk. The financial risk is based on balance sheet analysis, profitability analysis, cash generation analysis and liquidity analysis. The factors within each risk receive a score. These are then weighed in order to arrive to the total score for business risk and financial risk, respectively. Country risk and soft factors such as management and aggressiveness of financial policies, can limit the overall credit score. A committee makes the final decision on the scoring and lastly, the score is transformed into a rating code.

As mentioned in section 2.3, a rating code may be *official* or *unofficial*. The calculation of official rating codes is comprehensive as there are greater expectations to its accuracy. It will thus most likely include all factors illustrated in figure 2.1. Moody’s, for example, one of the largest CRAs in the world, employs a diverse group of credit risk professionals to manually *weigh* the factors implemented in a credit rating code. Moody's rating procedures are not based on a set of financial ratios already chosen prior to the analysis. Each target is individually analyzed based on individual needs. Moody's explains that the focus is not put on balance sheet values, but on identifying the assets' ability to generate and support future cash flow (Moody's). Figure 2.2 is an illustration of S&P's credit rating analysis process, depicting a vast information base behind each rating.

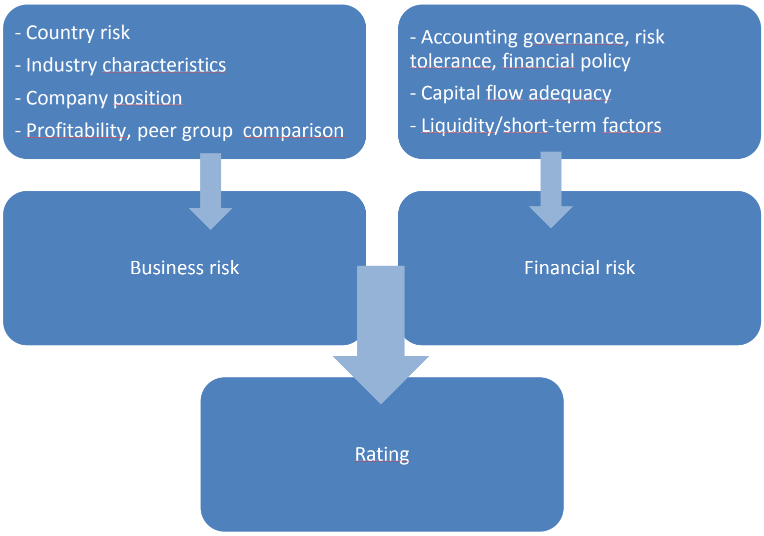

Figure 2.2 S&P's risk factors for corporate ratings

Source: (S&P, 2011)

On the other side of the scale, calculating unofficial rating codes, smaller players are more likely to rate companies based on much less information. Some may, for example, not have the resources or the need to employ a credit committee to change ratings manually.

2.4.1 Credit rating codes

Credit ratings communicate a company's creditworthiness to the market through credit rating codes. These codes are short, often only a number or a letter, quickly communicating the creditworthiness of an entity or an instrument. The applied code scheme may vary depending on the credit rater as well as the entity or item being rated. Remembering that the focus in this thesis is on company ratings, S&P uses the following scale for its long-term issuer credit rating (S&P b).

AAA, AA, A, BBB, BB, B, CCC, CC, R, D/SD, NR

From AA-ratings to CCC-ratings "+" and "-" are applied to create nuances and to enable comparison within the major categories. An entity receiving an AAA-rating is said to be very capable of meeting financial commitments. R is given to entities under regulatory supervision and D-rated companies are expected to default and to fail to pay all obligations. SD stands for selected default and is assigned when a company defaults on *selected* obligations. NR is assigned to non-rated companies.

Fitch (2014) applies almost the same scale.

AAA, AA, A, BBB, BB, B, CCC, CC, C, RD, D

From AA-ratings to B-ratings "+" and "-" are applied for the same reasons mentioned for S&P above. Fitch's rating codes describe "an entity's relative vulnerability to default on financial obligations" (Fitch, 2014). AAA stands for the lowest default risk and is only assigned to companies with exceptionally strong capacity to pay back on obligations. RD stands for restricted default, with a similar meaning as S&P's SD. It is assigned when a company's payments are overdue, but the company has not yet entered any bankruptcy filings. When given a D-rating, a company has ceased business and entered bankruptcy filings.

Moody's scale is built up like the following (Moody's, 2009).

Aaa, Aa, A, Baa, Ba, B, Caa, Ca, C, NR

1, 2 and 3 are applied as modifiers to rating codes Aa to Caa to show further differences between companies. The ratings reflect the probability of default, where Aaa-rated companies are the ones with the lowest credit risk. NR stands for non-rated companies.

From looking at the rating scales above it is obvious that the big three have copied each other to some extent. These letters are understood and recognized around the world as signals of credit risk. A common "language" for discussing credit risk has evolved, and so the scales stay quite similar. Bisnode, a smaller business information provider, uses AAA, AA, A, AN, B, C. Bisnode's scale is elaborated upon in section 3.5.2. Experian uses a scale from 0 to 100 (Experian b). This scale is a joint European standard scale. Both limited and responsible companies as well as sole proprietorships are rated by Experian's "expert model”. The number of points are divided into groups, where the companies with the highest score have, according to Experian, the best creditworthiness. The scale looks like the following.

1-14, 29-15, 30-49, 50-74, 75-100

The codes are important for players evaluating credit risk as they communicate a vast amount of information quickly and in an aggregated manner. Investor regulations and guidelines are being constructed based on rating codes. A rating downgrade can have critical effects on a company when made public. Investors may, for example, decide to withdraw investments, sell out or demand a higher interest rate on extended credit. Due to the importance of avoiding a rating downgrade, monitoring services offered by credit evaluating bureaus are proven very popular. This gives the rated companies a chance to cooperate with the rating agency and to introduce necessary proactive changes to hinder a downgrade before execution.

In the world of credit ratings, one may come across a rating code being referred to as “investment grade”. This indicates that the rating is of a high level and it has become a symbol of quality. Using the scale of the big three, it means that a rating code is BBB or higher for S&P and Fitch and Baa or above for Moody’s. This “threshold” is known to every player in the credit industry. A rating code below BBB/Baa is referred to as “junk”. Due to the increased risk taken by investing in “junk” companies, a higher return is also required. A rating code downgrade can have serious consequences for an entity, especially if the downgrade is from “investment grade” to “junk”. For example, portfolio manager performance may be benchmarked against credit rating codes and they might be obliged to withdraw investments if a downgrade turns an investment into “junk” (de Haan & Amtenbrink, 2011).

Below, in figure 2.3, follows S&P’s credit rating code scheme, presented as an example of how each credit rating code is worded. The descriptions are verbatim quoted, followed by comments.

Rating	*Description*
AAA	An obligor rated 'AAA' has extremely strong capacity to meet its financial commitments. 'AAA' is the highest issuer credit rating assigned by Standard & Poor's.
AA	An obligor rated 'AA' has very strong capacity to meet its financial commitments. It differs from the highest-rated obligors only to a small degree.
A	An obligor rated 'A' has strong capacity to meet its financial commitments but is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than obligors in higher-rated categories.
BBB	An obligor rated 'BBB' has adequate capacity to meet its financial commitments. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.
BB	An obligor rated 'BB' is less vulnerable in the near term than other lower-rated obligors. However, it faces major on-going uncertainties and exposure to adverse business, financial, or economic conditions which could lead to the obligor's inadequate capacity to meet its financial commitments.
B	An obligor rated 'B' is more vulnerable than the obligors rated 'BB', but the obligor currently has the capacity to meet its financial commitments. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments.
CCC	An obligor rated 'CCC' is currently vulnerable, and is dependent upon favorable business, financial, and economic conditions to meet its financial commitments.
CC	An obligor rated 'CC' is currently highly vulnerable. The 'CC' rating is used when a default has not yet occurred, but Standard & Poor's expects default to be a virtual certainty, regardless of the anticipated time to default.
R	An obligor rated 'R' is under regulatory supervision owing to its financial condition. During the pendency of the regulatory supervision the regulators may have the power to favor one class of obligations over others or pay some obligations and not others.
SD and D	An obligor rated 'SD' (selective default) or 'D' is in default on one or more of its financial obligations including rated and unrated financial obligations but excluding hybrid instruments classified as regulatory capital or in non-payment according to terms. An obligor is considered in default unless Standard & Poor's believes that such payments will be made within five business days of the due date in the absence of a stated grace period, or within the earlier of the stated grace period or 30 calendar days. A 'D' rating is assigned when Standard & Poor's believes that the default will be a general default and that the obligor will fail to pay all or substantially all of its obligations as they come due. An 'SD' rating is assigned when Standard & Poor's believes that the obligor has selectively defaulted on a specific issue or class of obligations but it will continue to meet its payment obligations on other issues or classes of obligations in a timely manner. An obligor's rating is lowered to 'D' or 'SD' if it is conducting a distressed exchange offer.
NR	An issuer designated 'NR' is not rated.

Figure 2.3 S&P's long-term issuer credit rating codes

Source: (S&P, 2013)

The description of all rating codes containing A is very positive and the wording “strong” capacity is applied. When the rating code is downgraded one notch, to BBB, the capacity to meet financial obligations is only “adequate”. The rating is, however, still “investment grade”. For BB-rated companies the chance of the capacity being “inadequate” is introduced. The step from adequate to potentially inadequate is a large one, and the weakened trust is signalized by specifying the company as “junk”. A company rated B *currently* has the necessary means available, but the capacity will quickly “impair” if conditions change. CCC-rated companies need “favorable conditions” to survive. This entails huge risks, requiring large returns to cover it. When rated CC, S&P expects the company to default and acquiring credit become will be hard.

Many firms in need of access to market capital do as Statoil ASA, the largest firm in Norway, and purchase a solicited rating from one of the big three. Such a rating provides the access needed and may lead to favorable terms and conditions related to the capital, as trust towards a company increases with an official rating. Statoil ASA is rated Aa2 by Moody’s and AA- by S&P. Statoil ASA’s goal is to at least stay within the single-A category (Statoil ASA, 2013). Statkraft AS, another large Norwegian firm, is rated A- by S&P and Baa1 by Moody’s (Stenqvist, 2014).

2.5 Credit rating calculation by banks

Banks use credit rating codes as a financial decision making tool when evaluating (potential) customers. The method applied depends on the size of the bank and the resources available for risk calculation. Rating codes are also used for regulatory purposes. There are two main approaches to calculate the minimum requirement in a bank. There is the standard approach and the internal ratings-based approach, where the former applies external credit rating codes and the latter and more advanced method requires banks to internally calculate credit rating codes.

Credit rating codes used for internal customer credit assessments

There are many factors involved in a customer evaluation. Some examples on an aggregated level may make it easier to understand. The calculation of credit risk in Fana Sparebank in Norway depends on three decisive factors. These are payment capacity, security and payment willingness. The former refers to accounting information and the latter refers to "other business risks" (Fana Sparebank, 2012). Each parameter is given a risk class between A and E, where A is the best. Thereafter, the risk classes are weighed. Payment capacity is weighed 0.5, security 0.3 and payment willingness 0.2. Next, they are united as one risk class. The key indicators applied in the evaluation are received from Kim Lingjærde and listed below.

- Payment defaults
- Audit remarks
- Liquidity ratio
- Working capital in per cent of turnover
- Equity in per cent of total capital as well as compared to the industry average
- Profit margin compared to the industry average
- Interest-bearing debt in per cent of EBIDTA
- The age of the company
- The number of employees.

In addition to these indicators, banks include security in their ratings. Security can be interpreted as a "second way out" when measuring the risk of issuing credit (Flakke, 2010). As an extra safety is obtained without having to reduce the initial claim on the borrower, banks reduce their net risk. Security is a way of mitigating the information asymmetry problem between borrower and lender (Gonzales & Ozuna, 2012).

After the parameters are weighed, the final credit rating code of the corporate commitment is ultimately matched with a risk description. Risk is described as minimal for class A, small for B, medium for C, high for D and highest for E (Fana Sparebank, 2012).

Sparebanken Vest, a larger Norwegian bank, calculates its rating codes differently. Its ratings are based on *internal calculations* of probabilities of default. Their scorecard has 11 risk classes, A to K, all representing decision zones. The risk classes and the accompanying probabilities of default in percentages are documented in figure 2.4.

Risk class	*Lower limit, probability of default (%)*	*Upper limit, probability of default (%)*
A	0.00	0.10
B	0.10	0.25
C	0.25	0.50
D	0.50	0.90
E	0.90	1.50
F	1.50	2.75
G	2.75	5.00
H	5.00	10.00
I	10.00	25.00
J	25.00	100.00
K	100.00	100.00

Figure 2.4 Risk classes based on the probability of default

Source: (Sparebanken Vest, 2013)

The probability that a company assigned to risk class A defaults is only between zero and 0.1 per cent. As the risk class worsens, the probability of default slightly increases. Not until risk class H does a company have more than a five per cent probability of default.

The detected risk class is the groundwork when entering a more thorough analysis of the customer's earnings potential, downside potential and behavior. Next, the customers' security is evaluated, using the expected value in a realization situation. Mortgages in real estate are considered risk-reducing. Thereafter follows the decision regarding credit issuance and risk price. This multi-step approach shows that, even though two customers receive the same risk score (same probability of default), they can still be treated differently due to different security.

The relative probability of default, PD, together with the calculation of the relative loss given default, LGD, and the bank's exposure at default, EAD, allows the calculation of the expected loss, EL, which is then covered by incorporating it in the pricing of instruments (e.g. increasing the interest rate) as well as by putting aside provisions. Equation 2.1 and equation 2.2 show the calculation.

*EL (relative number) = PD * LGD* Equation 2.1

When multiplying the relative expected loss with the bank's exposure at default, EAD, the expected loss in an absolute number is uncovered.

*EL (absolute number) = (PD * LGD) * EAD* Equation 2.2

Credit rating codes used to calculate the minimal capital requirement

All banks in Norway except for DnB Nor Bank, Nordea Bank Norge, Sparebanken Vest, SpareBank 1 SR-Bank, SpareBank 1 SMN, SpareBank 1 Nord-Norge and Bank 1 Oslo are standard approach banks (Andersen, 2011). When using a standard approach for calculating the minimum capital requirement, the risk is reflected using *external* rating codes from one of the External Credit Assessment Institutions, as their own internal credit risk models are not considered sufficiently advanced. The Financial Supervisory Authority of Norway allows rating codes from S&P, Moody's, Fitch and Dominion Bond Rating Service to be used to stipulate risk weights for commitments where this has been made permissible (The Financial Supervisory Authority of Norway, 2009b). The various rating codes are then converted into S&P's rating scale and transformed into risk-weights. This applies to unstructured exposures. Figure 2.5 comprises risk weights in percentages (Kjelsrud & Andersen, 2007). In Basel I, from 1988, the risk weights were only stipulated based on the type of item being rated (sovereign, corporate, real estate etc.), but Basel II allows external credit rating codes to be included as well, increasing the quality of the calculation.

Risk Class	***S&P***	***Moody's***	***Fitch***	***Risk weights, states and central banks (%)***	***Risk weights, enterprises (%)***
1	AAA to AA-	Aaa to Aa3	AAA to AA-	0	20
2	A+ to A-	A1 to A3	A+ to A-	20	50
3	BBB+ to BBB-	Baa1 to Baa3	BBB+ to BBB-	50	100
4	BB+ to BB-	Ba1 to Ba3	BB+ to BB-	100	100
5	B+ to B-	B1 to B3	B+ to B-	100	150
6	CCC+ and lower	Caa1 and lower	CCC+ and lower	150	150

Figure 2.5 From rating categories to rating classes, long-term rating

Source: (Balthazar, 2006)

The far left column shows the risk classes and the next three depict the corresponding rating codes of the big three. The two columns to the right list the risk weights. The use of risk weights depend on whether the entity in focus is an enterprise (far right column), or a sovereign or central bank (second right column).

When using an internal ratings-based approach, the requirement is not based on the opinion of external CRAs, but on internal models with internal risk parameters. Implementing an internal ratings-based approach is quite resource demanding, and only implemented by banks that consider the benefits larger than the cost. The required capital in an internal ratings-based approach reflects the actual risk more accurately and is much lower compared to using a standard approach. Banks applying the internal approach may thus free up capital to employ alternatively. The standard approach is created to be applied by different banks despite varying risk profiles. This leads to the calculation of *higher* requirements.

The minimum capital requirement towards Norwegian banks is steadily increasing, reducing the access to capital. According to the Norwegian Central Bank governor Øystein Olsen (2013), one way the banks are reaching their target is by increasing their lending margins through increased interest rates. A bank may also reduce its *amount* of credit extended in order to reduce the capital requirement. This reduces the price competition, also leading to higher lending margins (Langberg, 2014), i.e. increasing the dependent variable in this thesis.

2.6 Potential control variables

In this thesis, the changes in the *interest rate* is sought to be explained by the *credit rating codes*. The theoretical framework regarding these two variables has been presented above. Despite consisting of a great deal of aggregated data, credit rating codes most likely do not explain the changes in a company's interest rate all by themselves. Thus, other explanations need to be considered. These "other" explanations take the form of control variables (Midtbø, 2012).

To choose the appropriate control variables, an understanding of the *components* of the interest rate is necessary. As can be seen in table 3.1 and table 3.2, the *debt to financial institutions* is the largest category of credit and thus assumed to be the most influential part of the relevant debt, leading to a focused search on the price of this type of debt.

Characteristics influencing the price of debt to financial institutions may be firm specific as well as industry specific characteristics. When analyzing the relationship between the interest rate and lending relationships, Petersen and Rajan (1994) proved that size, represented by the natural logarithm of the book value of assets, significantly influences the interest rate on a company's most recent loan. Audretsch and Mahmood (1994) used size to analyze post-entry performance of new firms. They found firm size, when represented as the number of employees, being positively related to the probability of survival. Fana Sparebank also considers the number of employees as an important factor when evaluating a customer's creditworthiness.

The Norwegian Bank's SEBRA-model is a credit evaluation model, analyzing banks' credit risk towards the business sector (Eklund, Larsen, & Bernhardsen, 2001). In addition to accounting information representing earning capacity, liquidity and solidity, a company's risk of defaulting falls on the analysis of accounting numbers *compared* to industry averages as well as the age and size of a company. The ratios compared to the industry averages are the equity ratio, supplier debt ratio and the standard deviation of the earnings ratio. The denominator is always total capital.

The age is implemented by the SEBRA-model as the number of years since incorporation. The results show that younger companies default more often. The same is concluded by Svendsen (2005) in his article regarding characteristics of bankruptcy. Causes identified by Eklund, Larsen and Bernhardsen (2001), are, that new companies do not have the same competency, access to capital or ability to establish profitable business relationships as more mature institutions have. When adding size to the analysis, the SEBRA-model chooses the sum of assets. The results showed that the *next* youngest companies default the most. One reason may be that the youngest companies do not have enough bankruptcy estate to make a bankruptcy filing sensible (Eklund, Larsen, & Bernhardsen, 2001).

Fana Sparebank also uses accounting information when evaluating customers' credit risk, assisting the bank in the pricing of loans (Fana Sparebank, 2012). However, accounting information only accounts for 50 per cent of the foundation when calculating a customer's risk class. Furthermore, Fana Sparebank evaluates payment defaults and audit remarks. Information in their annual report regarding credit evaluation components is scarce, but it is natural to assume that an increasing number of payment defaults and audit remarks lead to a more negative credit evaluation and thus higher interest rates. Age is also considered by Fana Sparebank.

Credit may also be extended based on various covenants. A covenant is an "undertaking given by a borrower to its lender to maintain a minimum or maximum level of a financial measure such as gearing or net worth or interest cover" (Moir & Sudarsanam, 2007, p. 151). Strict covenants may reduce the level of the required interest rate. Covenants are more often applied to long-term debt (Moir & Sudarsanam, 2007), which may contribute to weaken the assumption of the long-term debt having a higher interest rate.

Security is also mentioned as influencing the price of money. The same applies to security. A credit extender can take security in, for example, the borrower’s real estate. If the borrower defaults on his payments, the credit extender may sell the real estate to cover his losses. The more security a borrower can offer, the lower the interest rate may potentially become. Banks with internal credit evaluation methods often have information on a debtor’s security opportunities. An example is Fana Sparebank, weighing security 30 per cent in their internal credit rating model.

Edward I. Altman developed a bankruptcy model called the Z-score model (Altman, 1968). The original model includes five parameters, describing the chances of a company going bankrupt or not. Most of Altman’s ratios are based on accounting data, representing liquidity, profitability, leverage, solvency and activity ratios (Altman, 1968).

Considering a company’s main banking relationship would be of interest in order to detect potential differences in the level of interest rates offered by various banks. Macroeconomic characteristics may also influence the interest rate. They influence the supply and demand of credit and include parameters such as changes in income and inflation (Levy & Bar-Niv, 1987), as well as the money market rate. Levy and Bar-Niv (1987) found that increased variations in income and an increase in inflation lead to an increased probability of company default. It is also expected that the interest rate increases as the nibor increases.

2.7 The hypothesis, elaborated upon

The hypothesis behind the research question is, as mentioned, that there is a statistically significant and inverse relationship between creditworthiness and the interest rate. Now that the theoretical framework has been presented, this hypothesis and its underlying assumptions can shortly be elaborated upon.

Firstly, why would there be a relationship between the average interest rate of a company and credit rating codes? Their common factor is credit risk. The codes are built on perceived levels of credit risk and so are the interest rates assumed to be, regardless of whether the credit risk evaluation was executed internally or externally.

Secondly, why would the relationship be of an inverse nature? As creditworthiness increases, the interest rate is assumed to decrease. Increased creditworthiness implies that the credit rating code assigned becomes more favorable. In other words, the credit rating code is moving in the direction of AAA. If a company is able to achieve a more favorable credit evaluation, this is expected to be reflected in the cost of debt. The reason for this expectation is that risk aversion is assumed to be fundamental in the average Norwegian mind-set. The association is thus; the higher the credit risk, the higher the probability of default, the lower[6] the credit rating code assigned, and the higher the relative interest cost.

Thirdly, why should the inverse relationship be statistically significant? The interest rate differences should be large enough to rule out arbitrary differences. This helps to establish that the detected differences truly are a result of the credit rating codes and it also minimizes the risk of false conclusions.

A broad angle was applied when reviewing the theoretical framework on the topics of this thesis. The focus now narrows down on the variables relevant for this report's analysis. Information regarding the data set follows, centering on the selection process leading to the formation of the sample, which all further analysis is based upon.

[6] A "lower" code means a less favorable code.

3. Data

The data set is the core of this thesis, enabling the investigation of the research question. The data, the selected sample and the methods applied in the statistical analysis are elaborated upon.

3.1 Introduction to the data

A data set with company information is applied to support the investigation of this paper's research question: *does increased creditworthiness lead to reduced interest rate?*.

The data has been delivered yearly to the SNF and NHH by The Brønnøysund Register Centre via Bisnode D&B Norway and Menon Business Economics AS (Berner, Mjøs, & Olving, 2013).

All Norwegian public and private companies from 1992 to 2011 are covered by the data set. In total, there are 3 179 684 company observations and 101 010 group company observations (Berner, Mjøs, & Olving, 2013), organized as yearly panel data. The data set includes quantitative accounting information as well as qualitative facts. The former is found in the income statements, balance sheets and self-generated variables. The qualitative facts cover company facts and industry facts.

The income statement shows an overview of the income and expenses of a company, including the interest cost relevant in this thesis. The balance sheet portrays the assets a company owns and how they are financed. Examples of the self-generated variables are interest-bearing debt, the equity ratio, the tax rate and earnings before interest, tax, depreciation and amortization (EBITDA). The former is applied in the generating of the dependent variable, the interest rate. The accounts consist of singular posts as well as summation posts. All numbers are plotted in thousands, which they continue to be in this thesis.

Some of the company facts are company names, addresses, legal forms, year of incorporation, credit rating codes and the number of women on the board of directives. The industry facts include the main, secondary and third industry code as well as industry descriptions.

Both the accounting data and the facts have had to undergo extensive processing in order to be of use to the collectors. Processing and quality controls of the information in the data set are conducted and published in a public document. This document is called "*Working Paper 18/2013 Norwegian Corporate Accounts - Documentation and quality assurance of SNF's and NHH's database of accounting and company information for Norwegian companies"*[7]. The data base has been developed in order to create a basis for research executed by SNF and NHH members, both researchers and students. The purpose of the working document is to inform the users of the opportunities and limitations of the data. It has been of great help when writing this thesis.

In addition to the quantitative data set, interviews were performed in order fill in the gaps where needed. Direct contact was made with Bisnode, obtaining more detailed information than available in the working paper and on Bisnode's web pages. This was done as the credit rating codes play an important role in the thesis as the explanatory variable. January 29th, an hour long telephone conversation with the Discipline Manager in the credit department of Bisnode, Per Einar Ruud, was executed. This initiated further contact, consisting of short e-mail dialogues occurring from February through March. The questions were of a direct nature, leading to the detection of various key indicators built into their credit default model.

February 14th, a two hour long meeting was conducted with the Head of Finance at Fana Sparebank, Kim Lingjærde. The purpose was to acquire knowledge on the bank's credit rating procedures. The topics mostly regarded the minimum capital requirement, the bank's credit risk and the upcoming Basel III guidelines. Rating codes made public by banks are not a large part of the thesis, nevertheless, it contributed to the theoretical framework. Also here, subsequent e-mail contact was held.

March 25th, e-mail contact was initiated with Steinar Carlsen, Chief Executive Officer, CEO, of Hard Rocx AS. This was the company with the largest interest rate value. Carlsen was presented with the interest rate calculation and was asked to contribute with information to clarify the extremeness of their interest rate value.

[7] The Norwegian version was applied. The Norwegian translation of this document name is found in the bibliography.

3.2 Processing

Between 1992 and 2011, several accounting standard changes occurred, influencing company data. The largest change was implemented in 2005 when the European Union decided that companies listed on the stock exchange had to prepare group company accounts based on International Financial Reporting Standards, IFRS. This accounting standard is more balance oriented than the Norwegian income statement focus.

After receiving the data, representatives of SNF and NHH started processing it in order to make it user friendly. The latest “update” was made available in 2013 by Endre Berner, Aksel Mjøs and Marius Olving. As a new accounting law was issued in 1998, the procedure of reviewing the data was split into two parts. Data from 1992 to 1998 and from 1999 to 2011 were processed separately.

The data has been labeled according to the Norwegian accounting law of 1998 in order to increase consistency and standardization. However, as different companies implement accounting standards at different times, complete consistency over time and between companies is not considered realistic. Details on the processing of the data in view of the accounting standard changes have not been documented in the working document as the work was too extensive.

When the information available from the data base was too scarce, the SNF and NHH representatives extracted details from annual reports’ notes. In addition, information was extracted from the following sources

- Industry information from Statistics Norway
- Default information, accounting standards, auditors, accountant and structure of the boards from The Brønnøysund Register Centre
- Information regarding listed companies from Børsprosjektet (NHH’s data base for companies listed on the Norwegian stock exchange)
- Laws regarding the statement of accounts from The Norwegian Accounting Act
- Nibor from the Norwegian Central Bank.

3.3 Quality check

In order to evaluate the effects of the changes in the Accounting Act of 1998 and the transition to IFRS in 2005, several company accounts were checked for deviations between information in the data base and the annual reports. This enabled the discovery of input errors as well as the opportunity to generate new variables where large changes were detected.

Most missing variables were detected in residual posts. As accounting information was copied *directly* into the dataset, the summations were, nevertheless, considered correct. Missing variables mostly belonged to the time period 1992 to 1998, and new variables were generated. There is thus some uncertainty around the content of these generated variables. An overview of the detection of missing variables is presented in the working document. For each year it shows if data are *missing* or if there are simply *few recorded observations*.

On the one hand, it is stated that the sample used to verify mistakes is too small to conclude the data base's error rate. On the other hand, no sign of *systematic* deviations was detected; accordingly, the significance of the mistakes is considered small.

Without any further changes, the typical company looked like the one in figure 3.1, averaged over all years. The numbers are in thousands.

Income statement	
The result of the year	1733.13

Balance sheet[8]			
Current asses	34 927.56	16 763.43	Equity
Fixed assets	29 522.77	31 405.12	Short-term debt
		16 281.93	Long-term debt
Sum	64 450.33	64 450.48	

Figure 3.1 The average company in the data set, prior to changes

The results after the trimming of the data set can be seen in figure 3.2.

3.4 Selection of relevant data – creating the sample

In order to serve the purpose of answering the research question in this thesis, a sample of the population was chosen based on several criteria. Firstly, a short overview of the criteria

[8] With rounding errors.

is presented. Thereafter, more detailed information explaining the reasons behind the choices follows.

Observations with the following characteristics were excluded from the data set[9].

- No credit rating (1)
- No/negative *interest rate* (2)
- Inactive/bankrupt/terminated/ companies (3)
- Group associated companies (4)
- All company structures except for limited liability companies, as well as publicly owned companies (5)
- Companies within the “Finance and Insurance” or “R&D” industry (6)
- Other missing data (7)
- Obvious input errors (8)

1) Available credit rating codes for all observations

The credit rating code is the independent variable and thus needs to be represented in the sample. The only years for which rating codes are available are from 2005 to 2011. The years 1992 to 2004 are thus excluded. In addition, all companies that have not received a rating code at all are excluded.

2) All companies have positive interest rates

The interest rate is the dependent variable and this report concerns companies that are indebted and that pay interest costs. Observations with negative or zero interest rates are thus excluded. In effect, this removes companies with negative or zero in interest costs and interest-bearing debt.

3) All companies are active players on the market

In this thesis, healthy companies able to act out their core activities and at least reach *some* positive sales income are target companies. For this reason, companies labeled inactive as well as companies labeled bankrupt or terminated, are excluded. Companies registered with a year of bankruptcy are also excluded, despite the fact that some of them have survived after the filing. Companies with fundamental posts such as *sum of current* or *non-current*

[9] The numbers link the characteristics to further explanations below.

assets or *sum of short-term* or *long-term debt* below zero, are excluded. The same goes for companies with no positive *sales income* or *equity*. This is done in order to exclude companies that are labeled active, but that still do not perform any business. The analyses thus involve companies providing enough information for Bisnode to make sound credit ratings[10].

4) No companies are affiliated

Group-credit ratings may affect the interest rate of the subsidiaries as the group can vouch for the payment capacity of the subsidiary. The activities of the subsidiaries may also influence the credit rating of the parent companies. They are thus both, together with *affiliated* companies, excluded from the sample.

5) All companies are of the type *private limited liability company*

Companies that are not *limited liability* companies are excluded. When choosing one group to focus on, the conclusions drawn can better explain the behavior of this specific group. All limited liability companies are assumed to be profit maximizing. The same cannot be said about partnerships, sole proprietorships, public companies or observations where the company category is not clearly defined. These are thus excluded. Within the chosen category there are limited companies (AS/BA), publicly limited companies (ASA) and Norwegian-registered foreign enterprises (NUF) and these are assumed to share similar behavior patterns. Companies with public "ownership structure" above 50 per cent were excluded.

6) Certain industries are excluded

The industries "finance and insurance" and "research and development" are excluded as the characteristics of their assets are often very different from any other industry's assets. This refers particularly to the non-physical substance of the assets.

[10] Note that assets and debt are allowed to be zero (as long as interest-bearing debt is above zero, which it is), but sales income and equity have to be positive (because zero in these two variables means no activity).

7) All observations with missing posts are excluded

After the selections above were executed, a missing values-table was generated. If an observation (a company) had a missing value in one of the variables applied in the analysis, the entire observation was removed from the sample[11].

8) Obvious input errors are altered

Some observations had a year of incorporation equal to 1.99, 2.00 and 2.01. Assumptions were made and these values were altered to 1999, 2000 and 2001, respectively.

After executing the selections above, the sample fit the purpose of this report better. To finalize the processing of the data, a closer look at influential values was deemed necessary.

3.4.1 Influential values

Regression analysis is the chosen tool for the statistical analysis of the data and variables with very large values can influence the regression coefficients severely (Watson & Stock, 2012). This may lead to large model residuals (the difference between observed and predicted values). According to Midtbø (2012), various influential values may have reduced credibility and should be examined. Some large balance sheet summation posts in the data set were compared against relevant annual reports and proven true (i.e. they were not input errors). Regardless, their deviation from the mean value was too large and thus not welcomed as a part of the sample.

There are several solutions to reducing the impact of influential values. They can be removed or their impact can be reduced. When reducing their impact, winsorizing is possible (Ghosh & Vogt, 2012). Winsorizing can be performed using different “cut-off”-points. When winsorizing at the *95 percentile,* five per cent of the highest and the lowest observations are not removed, but given the *same* values as the values at the cut-off points. The observations are thus not deleted entirely, but the influential power of their values is reduced. An advantage is that none of the data are removed. It does however give a wrong impression of the frequency of values. They also still influence the results considerably. Imagine an interest rate being one per cent, but entered incorrectly as 100 per cent. It would then be considered better to remove it, than keeping it at a cut-off rate at, say, 50 per cent.

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[11] An exception is the liquidity ratio compared with 74 permissible missing values, more information in section 4.1.2.

When eliminating variables entirely, specific values may be identified and excluded, or cut-off points may be applied.

In this thesis, the largest interest rate value observed was 8 356 per cent. The company's average interest-bearing debt was NOK 9 000 and their interest costs were NOK 376 000 (376 000 / 9 000 = 8 356 per cent). In this case, it is obvious that the correlation between the numerator and the denominator is not a healthy one and contact was made with the company's CEO, Steinar Carlsen, to increase the understanding of the results. This company has large overdraft facilities (credit lines) between January and August each year and pays back the amount within August. The debt is thus not visible in their balance sheets and the interest rate calculated in this thesis becomes unrealistically large. This is just one of many possible reasons for the large interest rate values in the data set. As the rates were generated by the author of this thesis, they do not always coincide with the true values. More information on this follows in section 3.5.1 and 3.8. In order to remove the largest and probably untrue interest rates, all interest rates above the 95 percentile limit were removed.

Not only the generated interest rate, but also most other variables, had extremely right skewed distributions. This means containing extremely positive values leading to a distribution with a right tail. The same trimming process was thus also performed on the following list of variables.

- Sum of current assets
- Sum of non-current assets
- Sum of short-term debt
- Sum of long-term debt
- Equity

As the analyses were executed yearly, so was the trimming.

Succeeding all changes, the typical company looked like the one in figure 3.2, averaged over all years.

Income statement	
The result of the year	154.63

Balance sheet[12]			
Current asses Fixed assets	1425.72 1032.54	692.25 903.94 862.08	Equity Short-term debt Long-term debt
Sum	2458.26	2458.27	

Figure 3.2 The average company in the sample, post changes

The sum of assets is only 3.814 per cent of what it was in the original data set, reducing the spread of the values of the companies and leading to a sample dominated by smaller companies.

3.5 Selection of relevant variables

After the process of selecting functional and appropriate data for the study, the dependent and independent variables along with the control variables are now presented.

3.5.1 The dependent variable, the interest rate

The interest rate has, as mentioned, been generated by the author of this thesis. The interest cost was divided by the interest-bearing debt. The question is; *which parameters are the best to represent the relevant interest cost and the relevant debt in the best possible way?*

In the income statements there are two interest cost posts. *Interest cost within the group* and *interest cost*. Only the latter is included, as group companies and subsidiaries are not a part of this analysis. The *interest cost* post also includes *other interest costs*. Any further specification is not available. This limits the depth of analysis and is important to keep in mind when interpreting the results. The aggregated post *financial costs* is not applied as it includes impairments, other financial costs and losses due to currency exchange. These posts are not a part of the relevant analysis.

Regarding the relevant debt, the SNF and NHH have already derived two *total interest-bearing debt* parameters through employing the accounting numbers. These are *total interest-bearing debt maximum* and *total interest-bearing debt minimum*. The former is calculated by adding all debt and subtracting non-interest-bearing debt. The latter is calculated by adding all debt that is guaranteed to be interest-bearing (Berner, Mjøs, &

[12] With rounding errors.

Olving, 2013). Despite the fact that these are simplified measures and may not be the true interest-bearing debt, they represent the best possible measures. The maximum and minimum calculations are very similar, and the choice of variable does thus not affect the analysis in a significant way. In this thesis, the minimum debt calculation has been chosen. The average of the opening and closing balance is applied. Below follows the interest rate calculation.

$$The\ average\ interest\ rate = \frac{2 * interest\ cost}{total\ interest - bearing\ debt\ minimum\ (OB + EB)^{13}} \tag{3.1}$$

When generating relative variables, it is important to consider the match between the numerator and the denominator. *Total interest-bearing debt minimum* includes *short-term group debt* and *long-term group debt.* Group information should not be a part of our data set. The parent companies, subsidiaries and affiliated companies are, however, already excluded. Group information is thus neither to be found in the numerator nor the denominator. It should be mentioned, that the match between the interest costs paid and the interest-bearing debt is still not guaranteed.

The interest-bearing debt, upon which the interest rate in this paper is based, is an aggregated post containing the following long-term posts.

- Long-term convertible loans
- Bonds loans
- Long-term liabilities to financial institutions
- Subordinated loan capital
- Unspecified long-term financial debt

The short-term posts follow.

- Short-term convertible loans
- Short-term market financing
- Short-term liabilities to financial institutions

[13] OB = Opening balance and EB = Ending balance.

In order to try to understand what determines the size of the interest rate, the size of each of the abovementioned interest-bearing debts are displayed in table 3.1 and table 3.2.

Table 3.1 Long-term interest-bearing debt categories, amount per year

Accounting year	***Long-term debt***				
	Convertible loans	**Bond loans**	**Financial institutions**	**Subordinated loan**	**Unspecified financial debt**
2005	2.153	3.305	484.352	3.953	255.369
2006	1.953	3.694	530.621	4.099	265.695
2007	2.691	4.412	568.815	0.763	244.830
2008	2.645	6.006	620.405	1.255	239.552
2009	2.694	5.715	610.594	2.547	209.418
2010	2.654	4.886	627.846	2.964	226.993
2011	3.696	5.867	648.394	3.287	220.923
Average	2.648	4.839	584.379	2.728	236.908

Table 3.2 Short-term interest-bearing debt categories, amount per year

Accounting year	***Short-term debt***		
	Convertible loans	**Certificates**	**Financial institutions**
2005	1.177	0.416	70.662
2006	1.624	0.760	74.560
2007	2.691	0.637	72.555
2008	2.645	0.706	75.349
2009	2.694	0.587	66.674
2010	2.654	0.598	67.424
2011	3.696	1.020	71.370
Average	2.456	0.672	71.058

Clearly, the long-term and short-term liabilities to financial institutions and unspecified long-term financial debt are the most influential factors. The unspecified debt is unfortunately not a good basis for interpretation. Mostly, long-term liabilities are promissory notes, mortgages and construction loans, whereas the short-term liabilities are time-limited loans, time limited loans in foreign currency and lines of credit given by banks.

Naturally, the calculation of the interest rates on the various liabilities vary, but due to the domination of the liabilities to financial institutions, it is normal to assume that interest rates set by banks etc. play a large role in the estimation of the average interest rate per company.

3.5.2 The independent variable, the credit rating codes

The credit rating codes are calculated by the business information provider Bisnode Dun & Bradstreet. The rating system is called the *AAA-rating system*, or *the expert model* and is designed to rate Norwegian companies. According to Per Einar Ruud in Bisnode, this system is created in order to calculate a company's probability of default. Both financial and non-financial parameters are added into the model. The calculations are mechanically performed.

Companies can buy access to the rating codes calculated by Bisnode, or the system can be purchased and integrated into internal credit assessment models. The system is updated whenever new information is available, thus always being up-to-date. The credit assessment is based on four pillars (Bisnode Norway). Additional information below each pillar is added where appropriate, based on information received from Per Einar Ruud.

- Basic facts about the company
    - Age- two years defines *established* companies and five years and above defines *well-established* companies (from the year it was registered in the register for business enterprises)
- Information on the owner and judicial aspects
    - Mostly applied to newly established limited companies without accounts. Private information regarding the chairman and the CEO, is examined.
    - Ownership structure
    - Company structure
- Key indicators and economic aspects
    - Key indicators

        - Profitability, interest coverage, return on assets and changes in return on assets
        - Liquidity, long-term financing of stock, working capital and liquidity ratios 1 and 2
        - Financing, loss buffer, equity ratio and share capital
    - Economic aspects
        - Audit remarks
- Payment history
    - Payment defaults from collection agencies and public registers. The amount due, maturity of the debt and the type of default as well as the total amount against the equity is considered.

Following each topic are decision trees with approximately 2500 rules (Bisnode Norway). Additional requirements for top rating codes are the following. In order to receive an AAA or AA, the company's turnover has to be at least NOK 1 000 000 or NOK 500 000 respectively and the equity has to be more than NOK 200 000 or 100 000 respectively (Bisnode Norway). Ruud specified that adding industry information as well as analyzing key indicators up against industry averages are improvement opportunities to make the codes more accurate. Bisnode's credit rating code scheme is presented in figure 3.3.

Rating	***Description***
AAA	This entity has a strong economy, is well established and has no registered payment remarks of importance or audit remarks. Sole proprietorships cannot achieve an AAA-rating.
AA	The characteristic of an AA-rated company is a well-established company with a good or satisfactory economy. There is no significant negative information registered on the entity.
A	An A-rated entity usually has a somewhat weak economy, but can still be considered as a creditworthy entity. No or insignificant negative information is registered on the entity.
B	A B-rated entity has a weak or bad economy. It has been operating at a loss and the equity is partially or completely lost. There is no negative information in terms of payment defaults registered on the entity.
C	This entity has a weak or bad economy and there is severe payment remarks registered. It can also be a newly established entity without accountings, but for which negative information is registered on the company, the CEO or chairman.

Figure 3.3 Bisnode's Expert Model

Rating	*Description*
No rating	This entity often receives payment remarks that are of significance for the future operation of the enterprise. Essential information on the company may also be lacking, which makes it impossible to to make a qualified assessment of the entity's creditworthiness.

Note: Translated from Norwegian by the author of this thesis

Figure 3.3 Bisnode’s Expert Model, continues

Source: (Bisnode Norway)

In comparison to the big three, Bisnode has fewer rating categories and no opportunity to nuance the rating codes. From the wording in the table, it is understood that a company receiving an AAA-rating or AA-rating is satisfactory within all areas. When going one notch down, to an A-rating, the economy of the company is described as “somewhat weak”. Subsequently, when a company is rated B, the economy is considered “bad”. A rating C is not received until there is “negative information” available regarding the company or the leaders of the company. One must not forget that companies with a C-rating may be newly established companies with start-up problems that might quickly be resolved. The codes are linked to each *company*, and not related to any *instrument* that the companies may hold.

None of the firms included in the sample have solicited ratings from any of the big three and none of them are listed on the stock exchange. There is thus less publicly available information on the relevant companies and, for this reason; the credit rating services offered by Bisnode are valuable.

The rating codes are categorical variables, thus included in the model as dummy variables, further explained in section 3.9.1. To access the files, the statistical program Stata has been utilized. The process of selecting relevant data as well as the generating of variables can be reviewed in attachment 7.6, where the Stata-commands are documented.

3.5.3 The chosen control variables

The choice of control variables in this thesis depends on what information the Bisnode credit rating codes already comprise, documented in the section above.

Firstly, size is added as a control variable. It is represented by the sum of assets. Another measure for size is the number of employees. This information is, however, not available for 2006 and 2007 and is thus not applied. The assumption is that larger firms receive more favorable terms when borrowing money than smaller firms. Having a large stock of assets may also indicate a greater opportunity for creditors to secure the loans. The size is averaged over the opening and ending balance and divided by 100.

Secondly, the year of incorporation is added as a control variable. Bisnode added a categorical dummy dividing companies into two groups based on age, young companies and old companies. In this study, a control variable representing the year of incorporation as a *continuous* variable is added with the expectations that older companies, being more well-established than newer companies, receive loans with more favorable interest rates.

Ratios representing earning capacity, liquidity and solidity are assumed already included in the Bisnode credit rating code. However, as Bisnode pronounced that they are considering adding more key indicators put up against industry averages, a company's liquidity ratio compared to its relevant industry average is also added as a control variable. The liquidity ratio is calculated as the current assets divided by the short-term debt. Both the value of the numerator and the denominator are averaged over the opening and ending balance sheet.

Industry is added as a fourth control variable. According to Mjøs and Phan (2011), the industry "real estate and services" lends the most, against security in real estate. It is thus assumed that companies within the real estate industry, the corresponding industry in the SNF's data set, pay the lowest interest rate. In the data set, industry is described by two industry variables. One created in 2002 and one in 2007. As the latter is newest and has less missing observations, this is chosen to represent the various industries.

The level of security, or the level of *mortgaged assets* as it is labeled in the data set, is assumed to affect the interest rate level. However, not enough information was available to apply it as a control variable. The same goes for covenants and information regarding banking connections. As already mentioned, the analyses are executed for each year separately, so variables changing over time are not suitable.

The chosen variables included in the further analysis are listed in table 3.3.

Table 3.3 The relevant variables

	Additional information
Credit rating codes	Categorical variables, added as dummies.
Size	Continuous variable, represented by the sum of assets, average of opening and ending balance sheet values, divided by 100.
Year of incorporation	Discrete variable.
Liquidity ratio compared	Continuous variable, represented by the average liquidity ratio divided by the relevant industry's average liquidity ratio. Current assets and short-term debt are averaged over the opening and ending balance sheet values.
Industry	Categorical variables, added as dummies.

The framework of the analysis first presented in figure 1.1 is now expanded and the relationship concentrated upon is the following.

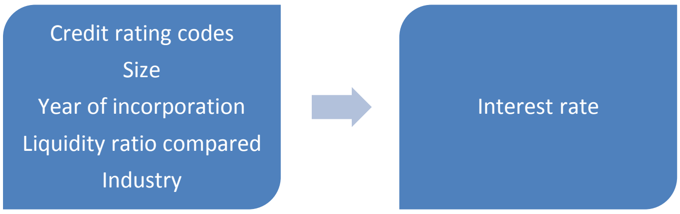

Figure 3.4 The foundation, expanded

Together with the credit rating codes in the left square of figure 3.4, the control variables have now been identified. In the right square, the dependent variable is presented.

3.6 Secondary data

The data applied are multiple-sourced secondary data. Secondary means that the data are collected by other people than the author of this thesis. Multiple-source means that they are collected using several sources and gathered into one data set before employed (Saunders, Lewis, & Thornhill, 2009).

An advantage using secondary data is that they are already available for analysis, thus saving resources. Another advantage is that the quality of the data collection is most probably higher than if the collection was self-executed. Disadvantages may be that the purpose of the collection differs from the user's needs (Saunders, Lewis, & Thornhill, 2009). As mentioned, the data has been collected in order to enable SNF and NHH members to perform research on Norwegian companies. This purpose is “wide”, thus not favoring any specific research question. On the one hand, this enables research with different goals to be performed on the same data set without any specific favoritism related to the collection of data. On the other hand, had the data been gathered for the sole reason of answering *this* report’s research question, additional information and variables would be acquired. Examples are more information regarding security, the number of employees, main bank connection, and less aggregated information regarding the various credits and the corresponding interest costs. However, all these factors are not publicly available, and they would have made the process quite demanding. It would thus not be a realistic choice when considering the time and resource limitations of a master thesis.

The two following sub-sections, *reliability* and *validity*, critically review the data and the methods applied to prepare the data for analysis.

3.7 Reliability

When measuring *reliability* of the data, the data collection and selection techniques are put under the loop. The topic of interest is whether the same results might be reached in other settings and by other researchers. The data collectors are members of SNF and NHH. These are serious institutions and the level of precision required by these actors is assumed to be high. The same can be said about the other sources listed in section 3.2 such as Statistics Norway and the Brønnøysund Register Centre. This increases trust towards the data set.

The data were not only collected, but also reviewed, by the same staff. The process and impact of this is well documented in the working document, increasing the reliability. The reliability connected to the time span 2005 to 2011 applied in this report increases even more as most of the missing data were detected between 1992 and 1998.

After acquiring the data, the author of this thesis applied sample criteria in order to prepare the data for analysis. Due to high transparency around the process in section 3.4 and 3.5, the reliability of these techniques is not considered a concern.

Some additional information was acquired through three interviews shortly described in section 3.1. The information derived from these interviews was facts and no interpretation of statements was thus executed by the interviewer. The information gathered is thus considered reliable and valid.

3.8 Validity

High reliability is necessary for data to have high validity (Hellevik, 1999). Validity deals with the questions *do the results truly say what they appear to? Is there truly a causal relationship between two variables?*

The independent variable is based on Bisnode’s default model. The dependent variable is a company’s average interest rate. To what degree a company is defaulting is assumed to be of importance when a creditor decides upon a suitable level of interest rate required. The probability of default also says something about the ability of a company to pay existing principals and interests. The causality between the two variables is assumed to be valid.

One of the concerns is the *validity of definitions*. This regards the leap between a theoretically defined variable and an operationally defined variable. The theoretical interest rate is, as mentioned in section 2.1 “the per cent of premium paid on money” (Fischer, 1930, pp. 13-14). The operational interest rate per company was not available in the data set and was thus generated in the best possible way. It was generated as the sum of *interest costs* derived in the income statement divided by the generated *interest-bearing debt* based on the balance sheet accounts. The interest cost is a summation of all interest costs paid throughout the accounting year. The generated interest-bearing debt variable is only a snapshot of a value at a point in time. In order to make the denominator match the numerator slightly better, the average of the opening and ending balance sheet debt values were applied. Nevertheless, the opportunity of miscalculating the average interest rate is present as a company may change the level of the debt whenever desirable. For example reducing debt just before the end of the year reduces the value entered into the balance sheets and leads to inflated interest rates. The amount of interest cost cannot be changed or manipulated in the same way. The trimming of data was executed in response to this.

Another issue is that each company carries equal amount of weight when calculating the average interest rates, even though the companies should be weighed according to the size of their interest-bearing debt.

One should also consider if there are other relevant control variables than those chosen (Hellevik, 1999). The number of control variables has been kept low. The ones included are mentioned across several sources, except for the liquidity ratio compared being added due to Bisnode’s consideration of variables compared to industry averages as potential improvements to their model. Due to the scope of this thesis as well as the limited access to relevant variables, other variables were not entered.

The time period analyzed is considered appropriate. The financial crisis was included and added an interesting aspect to the assessment as the impact of the rating codes increased when the financial crisis struck. More information regarding this is found in section 5.2.3.

Lastly, can the results be *generalized?* When deciding upon the potential degree of generalization of results, the selection criteria should be considered (Saunders, Lewis, & Thornhill, 2009). Of the 3 179 684 observations, only 89 405 are left in the sample. The results only apply to profit maximizing limited liability companies. Larger companies listed on the stock exchange are not expected to be influenced as much by Bisnode’s credit rating codes when already rated by one of the big three. The credit rating procedures are specific to Bisnode and also specific to ratings applied in Norway. It is rational to assume that similar results would be found in other countries, especially in the Nordic ones, but the effect of the financial crisis would most likely impact differently, as countries were struck differently. Overall the results extracted from this thesis are considered valid.

The presentation of the data is finished. In the following sub-section, the methods applied in order to arrive at the results are presented.

3.9 Methods applied in the statistical analysis

The goal of this thesis is to establish if there is a *causal relationship* between a company’s credit rating code, issued by an external business information provider, and its average interest rate. The research design performed can thus be said to be *explanatory* (Saunders, Lewis, & Thornhill, 2009). Whether a relationship exists is sought to be answered by applying regression analysis. This technique gives interpretable results based on statistical significance –a widely recognized method when analyzing causality.

The methods applied when *processing* the data are discussed in section 3.4 and 3.5.

3.9.1 Regression analysis

Regression analysis is an economic tool used to study the empirical correlation between variables (Biørn, 2009). It quantifies the cause and effect relationship between the dependent variable and each independent variable, holding other independent variables constant. A regression can have one or more of both independent and dependent variables. In this thesis multiple regression analysis with one dependent variable and several independent variables is applied. The formula for a linear multiple regression follows in equation 3.1.

$$Y = \beta o + \beta_i * X_i + \beta_j * X_j + \beta_k * X_k + \cdots + \varepsilon \qquad \text{Equation 3.1}$$

Y= The dependent variable

X= The independent variable

β_0 = The intercept

β = The coefficients

ε = The error term

$_{i,\, j,\, k\ldots}$ = specifying different variables and its corresponding coefficients

The intercept represents the value of the dependent variable when none of the independent variables on the right hand side has an effect on the dependent variable. Analyzing the intercept does not always add value when viewed in isolation. This especially applies if the coefficients of the added variables cannot be expected to be zero simultaneously. Then, the intercept is only thought of as the "coefficient that determines the level of the regression line" (Watson & Stock, 2012, p. 152). The other coefficients describe the effect (in what direction *and* how much) each of the corresponding independent variables have on the dependent variable, controlled for the effect of other included independent variables. The error term specifies all other factors explaining Y that are not included as an independent variable. The error term is always greater than zero (Wooldridge, 2006).

When the regression is based on a *sample* selected from a population, the regression formula looks like equation 3.2.

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_i * X_i + \hat{\beta}_j * X_j + \hat{\beta}_k * X_k + \cdots + \hat{\varepsilon} \quad \text{Equation 3.2}$$

The $\hat{\varepsilon}$-term is not the error term. It is the residual, calculated using the *sample*, but *representing* the error term in the *population* as the expected difference between them are zero (Wooldridge, 2006). The residual is the "difference between the observed values of the dependent variable and predicted variables based on the least squares coefficient estimates from a sample" (Berry, 1993, p. 27).

When running regression analyses, both predicted values as well as residuals are of interest. Addressing the residual sheds a critical light on the model and increases the validity of the results. The reviewing of the regression assumptions is documented in section 4.2.1.

The regression type used is called the Ordinary Least Squares, OLS. The OLS minimizes the sum of squared residuals (Wooldridge, 2006). The smaller the difference between the observed values (the values in the data set) and the predicted values (the values calculated by the regression formula), the better the model fits.

The null hypothesis, H_0, in a multiple regression analysis is that none of the independent variables significantly affect the dependent variable. The null hypothesis may be rejected if the F-value is above a certain threshold. The size of the threshold depends on the number of independent variables, the number of observations and the chosen significance level. A significance level is the chosen level at which the null hypothesis is rejected when it in fact is true (Wooldridge, 2006). In this thesis, the chosen level is five per cent. A five per cent chance of drawing the wrong conclusion is thus permitted. As long as *one* variable is significant, the F-value is above its critical value and the null hypothesis is rejected. The significance of the effect of each variable depends on the t- and the p-values. The t-value describes each coefficient's significance. If the test is two-sided using the five per cent significance level, the null hypothesis is that the corresponding coefficient may possibly be zero. Had it been one-sided the hypothesis would express in which *direction* the coefficient is thought to be significant. The absolute t-values have to be larger than 1.96 in order to reject the null hypothesis at a five per cent significance level (Wooldridge, 2006). This means that the coefficient's value is more than 1.96 times larger than its standard error of means. The standard error of means is a measure of the deviation from the calculated average value of the coefficient if a new sample was drawn from the population[14].

The R^2 is the coefficient of determination, describing how much of the variance in the dependent variable the model describes. When multiple independent variables are used, the *adjusted* R^2, R^2_{adj}, is a better measure, taking the increased complexity of the model into consideration (Midtbø, 2012).

Treatment of categorical variables in regression analysis

When adding categorical or ordinal variables as independent variables on the right hand side of a regression equation, the variables need to be transformed into "dummies". This applies to the credit rating variable and the industry variable. Dummies describe *qualitative phenomena* and thereby increase the quality of any study (Midtbø, 2012). One may use dummies to test if a regression is the same for two or several groups. Dummies take the values 1 or 0. For example, is the interest rate the same for a company with an AAA-rating as for a company with an AA-rating? In the regression, one dummy category must be left out as the "reference group". If the AAA-rating is the reference group and the coefficient of the AA-rating is positive (and significant), the interpretation is that companies rated AA have higher interest rates than companies belonging to the reference group AAA.

In order to investigate the difference between two credit rating codes where none of them are the chosen reference dummy, Stata's built-in tool, lincom, is applied. Lincom calculates the difference between two categorical variables and produces both the coefficient, the standard error of means, the t-value, the p-value and a confidence interval, just like a regression analysis does. Lincom is not applied on the industries as a detailed study of the effect of industry affiliation is not of interest.

The application of these methods has led to the results presented in the next section.

[14] Occasionally in this paper, the standard error of means is referred to as only "the standard error".

4. Results

4.1 Descriptive analysis

In this section, the characteristics of the variables are described; creating a greater understanding of the behavior of the variables. The behavior of the independent variables *compared to the interest rate* is also defined. This supports the results in the regression analysis, as their *causal* relationship is under the loop.

4.1.1 The dependent variable, the interest rate

The descriptive statistics of the interest rate is documented in table 4.1. Both the frequency as well as the central tendency, the spread and the skewness and kurtosis is described for all seven years. The mean, median, minimum and maximum interest rate as well as the standard deviation and the standard error of means are multiplied by 100, thus represented as percentages. The end column shows the *total* number when it comes to frequencies, whereas for the other results in the table, it shows the *average* value (i.e. the average interest rate and the average standard deviation). An exception is the median, which is simply the median and not an average value.

Table 4.1 Descriptive statistics on the interest rate per year

	2005	***2006***	***2007***	***2008***	***2009***	***2010***	***2011***	***Total/ Average***
Frequency	13 479	12 058	12 275	11 439	13 957	13 016	13 181	89 405
Mean interest rate (%)	6.683	6.569	7.811	9.415	7.759	7.199	7.157	7.485
Median interest rate (%)	5.941	5.926	7.252	8.960	7.350	6.705	6.646	6.935
Standard deviation (%)	3.695	3.614	3.809	4.310	3.937	3.783	3.726	3.940
Standard error (%)	0.032	0.033	0.034	0.040	0.034	0.033	0.032	0.013
Skewness	1.031	0.996	0.794	0.647	0.701	0.840	0.810	0.840
Kurtosis	4.196	4.104	3.995	3.999	3.736	3.934	3.871	3.967
Min. interest rate (%)	0.031	0.032	0.025	0.032	0.011	0.015	0.026	0.011
Max. interest rate (%)	20.225	19.391	21.015	24.277	21.395	20.351	20.000	24.277

The interest rate for limited liability companies has varied greatly from 2005 to 2011. The lowest average interest rate was observed in 2006, whereas it peaked in 2008. The difference between the highest and lowest mean interest rate is 2.846 per cent and the change occurred over only 2 years. The average interest rate quickly dropped again to 7.759 per cent in 2009 from 9.415 per cent in 2008, dropping even lower in 2010 and again in 2011. The mean is the average value of the *sample* and represents the expected mean of the *population*. The median is the central value, and is equal to the mean if the distribution is symmetrical around the mean (Wooldridge, 2006). If not, it is connected to skewness, further described below. As illustrated in figure 4.1, the sample mean always lies above the sample median. Large interest rate levels are increasing the mean but not affecting the median in the same way.

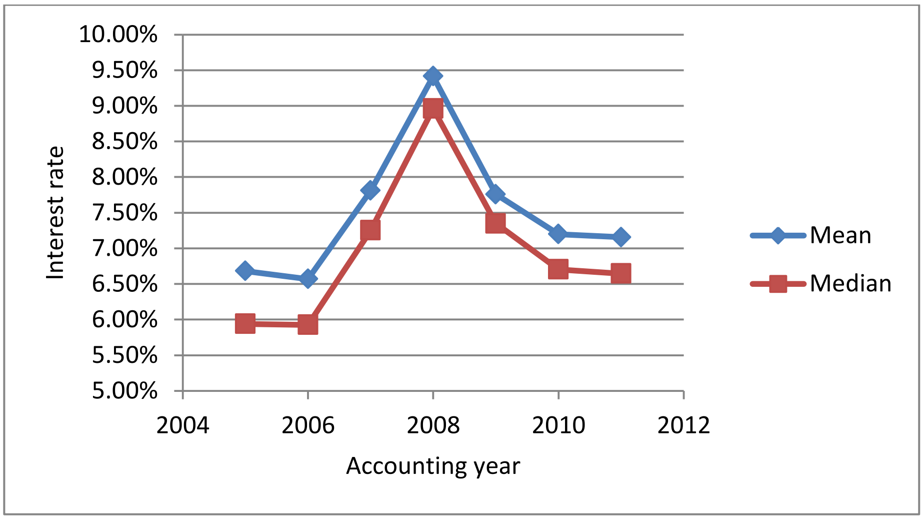

Figure 4.1 The mean and median interest rate per year

Information regarding an average value is often supplemented with information regarding the spread. Even though the mean interest rate in 2005 is 6.569 per cent, it does not automatically entail that all observations this year is close to this value. The standard deviation is the positive square root of the variance. It depicts the average deviation from the mean when choosing a random value from the sample, and thus expresses the interval in which a value of an observation lies. The interval depends on the significance level chosen. The interest rate's average standard deviation is depicted in table 4.1 as 3.940 per cent. When applying 68 per cent certainty, the value of a random observation lays within the interval *the average +/- one standard deviation*. With 68 per cent certainty, the value of an observation, averaged over all years, lies between 11.425 and 3.545 per cent; cf. table 4.1. This spread is broad and the variation within the sample's interest rate levels is thus high.

The standard errors of means portray how much the *mean* value would change if another sample had been chosen from the population. These are low, indicating small changes if other samples had been picked. The accuracy of the mean interest rate rests on the large amount of observations as the formula is $\sigma/\sqrt{n}$. σ is the standard deviation and n is the frequency of observations. In 2005, the mean interest rate at the five per cent significance level lay within the confidence interval of 6.619 – 6.747 per cent (calculated as the mean value +/- two standard errors).

The kurtosis and skewness describe the distribution of the variable. The kurtosis describes the thickness of the tail of the distribution as well as the size of the distribution's peak. If high, it is a sign of influential observations (Watson & Stock, 2012). In a normal distribution, the kurtosis is normally 3.000. The skewness describes the symmetry of the distribution. When the median is smaller than the average, this indicates right skewness[15] and the opposite is implied when the median is greater than the average. A normal distribution has a skewness of zero.

In figure 4.2, average interest rate observations from each year are illustrated in histograms. The X-axis shows the interest rates and the height of the histograms shows the frequency per interest rate. The overlying line represents a normal distribution. This figure illustrates the large standard deviations tabulated in table 4.1.

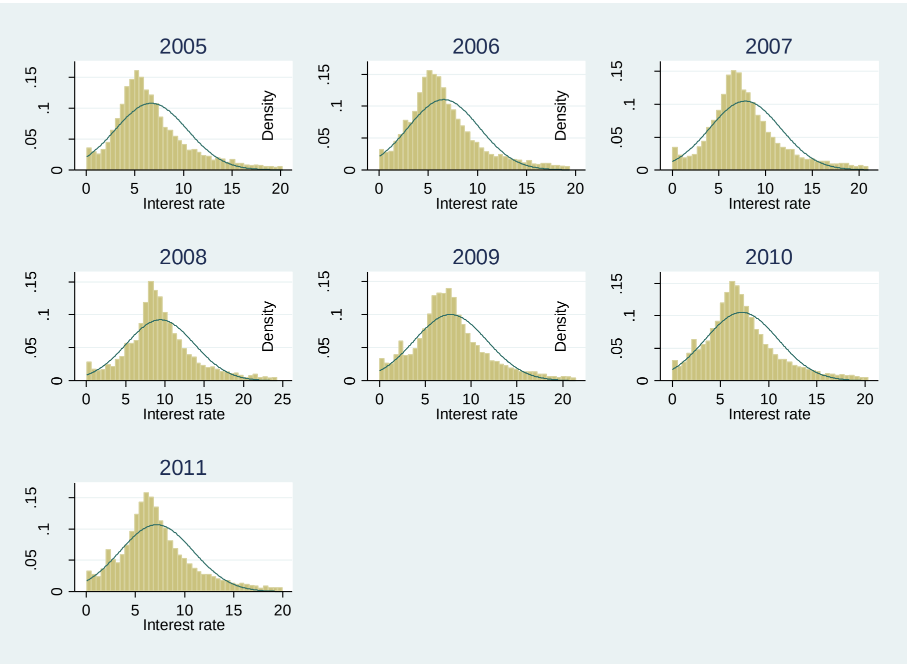

Figure 4.2 The distribution of the interest rate per year

[15] Also called positive skewness.

Table 4.2 also illustrates the skewness, ranging from 0.647 to 1.031, indicating a somewhat right-skewed sample. The kurtosis, ranging from 3.736 to 4.196, indicates a sharper peak than a normal distribution as well as thicker tails, signifying a presence of influential values.

4.1.2 The independent variables

The credit rating codes

The rating codes are categorical variables; therefore descriptive statistics are not suitable on the variable alone, except for frequency. In table 4.2, the frequency of the rating code as well as the development of the average interest rate over each credit rating code is displayed. The development is depicted using the mean, the standard deviation and the standard error, entered as percentages. The far right column depicts the *total* number of observations, and the *average* value for the other rows of information.

Table 4.2 Descriptive statistics on the interest rate per credit rating code and year

		2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*Total/ Average*
Frequency	**C**	118	73	125	130	228	161	241	1 076
	B	1 695	1 299	1 308	1 314	2 271	1 911	1 770	11 568
	A	4 157	3 668	3 489	3 560	4 006	3 771	3 572	26 223
	AA	5 783	5 126	5 268	4 749	5 649	5 383	5 576	37 564
	AAA	1 726	1 862	2 085	1 686	1 803	1 790	2 022	12 974
	Sum	13 479	12 058	12 275	11 439	13 957	13 016	13 181	89 405
Mean (%)	**C**	7.952	9.260	9.826	12.385	9.991	9.924	9.496	9.857
	B	7.475	7.401	8.698	10.483	8.826	8.275	8.136	8.445
	A	6.867	6.798	7.892	9.454	7.742	7.169	7.095	7.553
	AA	6.473	6.428	7.724	9.206	7.497	6.908	6.933	7.273
	AAA	6.084	5.819	7.215	8.859	6.988	6.744	6.745	6.908
	Mean	6.684	6.569	7.811	7.415	7.759	7.199	7.157	7.485
Standard deviation (%)	**C**	4.163	4.568	3.629	5.58	4.439	4.709	4.466	4.744
	B	3.818	3.875	3.781	4.656	4.173	4.056	3.990	4.184
	A	3.726	3.529	3.742	4.195	3.916	3.750	3.699	3.89
	AA	3.615	3.565	4.066	4.213	3.850	3.644	3.630	3.851
	AAA	3.550	3.480	4.506	4.198	3.801	3.554	3.450	3.768
	Mean	3.695	3.614	3.809	4.310	3.937	3.783	3.726	3.940
Standard error (%)	**C**	0.383	0.535	0.403	0.489	0.294	0.371	0.288	0.145
	B	0.093	0.108	0.112	0.128	0.088	0.093	0.095	0.039
	A	0.058	0.058	0.063	0.070	0.062	0.061	0.062	0.024
	AA	0.048	0.050	0.052	0.061	0.051	0.050	0.049	0.020
	AAA	0.085	0.081	0.079	0.102	0.090	0.084	0.077	0.033
	Mean	0.032	0.033	0.034	0.040	0.034	0.033	0.032	0.013

For each year, most companies are AA-rated companies. For all years except 2009 and 2010, the order is AA, A, AAA, B, C. In 2009 and 2010, however, there are more companies being rated B than AAA. See figure 4.3 for an illustration of the frequency of credit rating codes, averaged over all years.

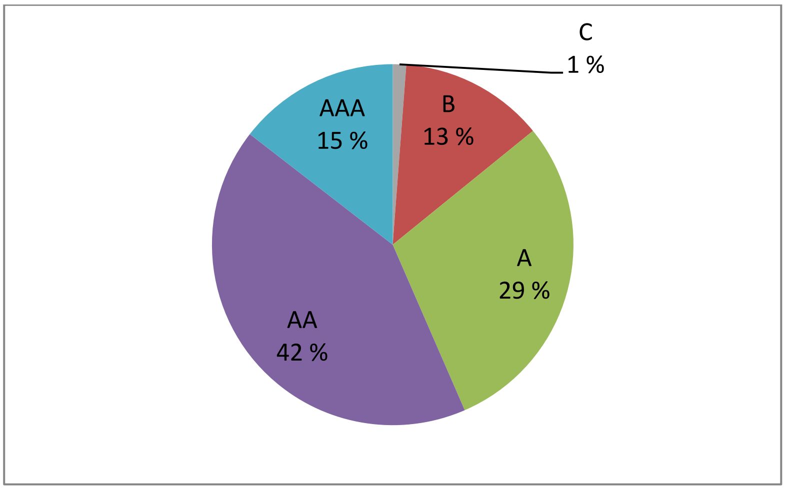

Figure 4.3 The average frequency per credit rating code

Figure 4.4 demonstrates the interest rate per rating code. Each line represents one specific credit rating code. The AAA-rating is the bottom line, indicating that companies rated AAA have, on average, the lowest interest rate each year. The line lying above the AAA-rating is the AA-rating and then follows the A-rating, the B-rating and the C-rating. The C- and the B-lines lie *noticeably* above the others, while the A- to AAA-lines ratings are closer to each other.

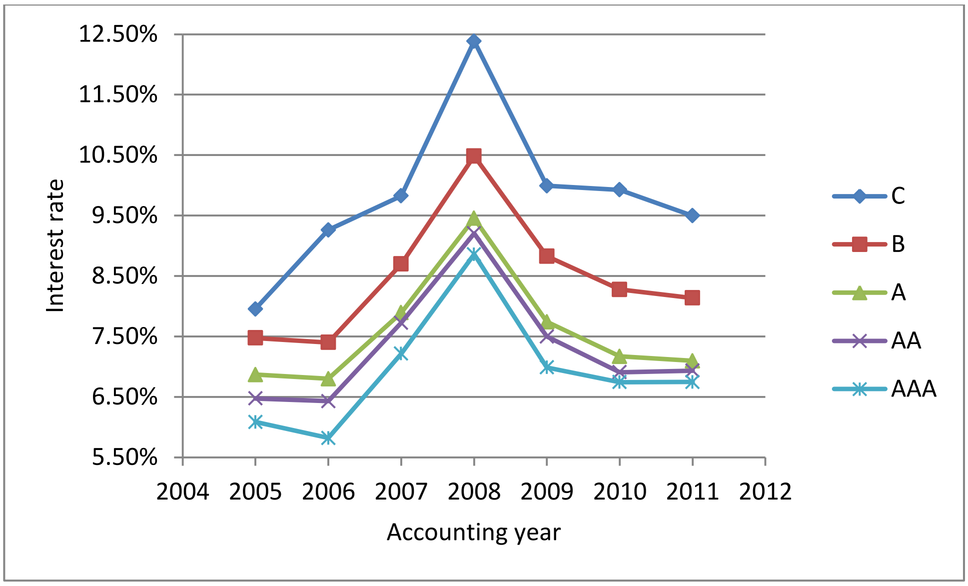

Figure 4.4 The interest rate per credit rating code and year[16]

Regarding the development over time, the rating codes clearly share the same pattern. Two exceptions are the average interest rate of C-rated companies increasing from 2005 to 2006 and the interest rate of AAA- and AA-rated companies slightly increasing in 2011. All average interest rates peaked in 2008.

There are quite large interest rate deviations *within* each credit rating code. This means that, even though it occurs as such on *average*, C-rated companies will not always have higher interest rates than B-rated companies etc. Regarding time, the deviations are largest in 2008 (looking at the standard deviation in table 4.2). Regarding the rating codes, companies rated C have the highest deviations. All rating codes have a minimum interest rate between zero and one per cent and a maximum interest rate of at least 18 per cent. This, together with large standard deviations, depicts large variations in the value of average interest rate observations for all credit rating codes. This is also illustrated in figure 4.5, where the X-axis is the interest rate and the height of the histograms represents the density. The results are averaged over all years.

[16] As the data are discrete, it can be argued that a histogram should be applied. However, a scatter diagram creates an informative impression of how rating codes influence the average interest rate compared to one another and over time.

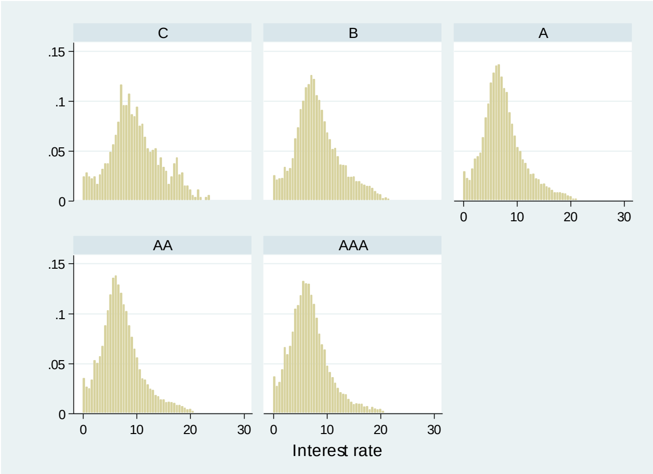

Figure 4.5. The spread of the average interest rate per credit rating code

The standard errors are very low for AAA- to B-rated companies with average values between 0.048 and 0.093 per cent. The average standard error of means of C-rated companies is larger, 0.383 per cent. As the description of the average interest rate of C-rated companies is based on much fewer observations, the uncertainty regarding the average interest rate is greater.

Year of incorporation

The year of incorporation[17] is a discrete value and descriptive statistics is of reduced value. Discrete means that the variable takes on a finite number (Wooldridge, 2006). It spans from 1853 to 2010 and has 111 unique values. The year with most incorporations is 2006.

Size

Size is a continuous variable, represented by the average of the sum of assets in the opening and ending balance sheet. Continuous means that it can take on any value (Wooldridge, 2006). Descriptive statistics can be found in table 4.3. The far right column depicts the *total* number of observations, and the *average* value for the other rows of information.

[17] The year of incorporation is consistently not called "age". This is because these two labels carry scales behaving in the opposite directions. Age goes from a higher value to a lower value (80 years old vs. 10 years old) when moving towards present time, whereas the scale of year of incorporation goes the opposite way, from a low value to a high one (1853 vs. 1900).

Table 4.3 Descriptive statistics on the size per year

	2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*Total/ Average*
Frequency	13 479	12 058	12 275	11 439	13 957	13 016	13 181	89 405
Mean (%)	2 093	2 309	2 413	2 529	2 435	2 509	2 598	2 410
St. deviation (%)	1 430	1 606	1 653	1 789	1 686	1 734	1 794	1 680
Standard error (%)	12.319	14.626	14.922	16.725	14.270	15.200	15.627	5.618

The average size of the companies in the sample is NOK 2.4 million. The standard deviations are very high, indicating large spreads in the value of the observations. The standard error is substantially smaller, indicating less uncertainty around the *average* size in the sample.

Liquidity ratio compared

The characteristics of the liquidity ratio are presented in table 4.4. The far right column depicts the *total* number of observations, and the *average* value for the other rows of information.

Table 4.4 Descriptive statistics on the liquidity ratio compared per year

	2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*Total/ Average*
Frequency	13 470	12 051	12 265	11 431	13 947	13 002	13 165	89 331
Mean (%)	0.707	0.918	0.937	1.011	1.09	1.088	1.241	1.000
St. deviation (%)	1.447	5.115	3.545	7.279	12.759	7.796	12.63	8.374
Standard error (%)	0.012	0.046	0.032	0.068	0.108	0.068	0.111	0.073

The reason for the difference in frequency in the far right column depicts the *total* number of observations, and the *average* value for the other rows of information.

table 4.4 and table 4.5 is that 74 liquidity ratio compared observations are “missing”. This is because the denominator, short-term debt, is zero for these observations (only observations with negative short-term debt were trimmed).

The liquidity ratio compared depends on the relationship between a company’s average current assets and its average short-term debt as well as the value of the average liquidity ratio per industry. The average liquidity ratio compared is 1.000. Averaged over all industries and years, the companies seem to have liquidity ratios similar to their peers. However, the large standard deviations tell the reader that there is a large spread in values. These deviations are even bigger than the average values. 71 156 observations have a liquidity ratio compared lower than one but only 18 175 have a ratio above one. Thus, certain companies have *very* large values, increasing the average liquidity ratios compared. The standard errors of means are quite low, indicating less uncertainty around the value of the mean liquidity ratio compared, had another sample been picked from the data set.

Industry

Industry is a categorical variable, similar to the rating codes, with 12 categories. In table 4.5 the frequency of observations per industry as well as information regarding the average interest rate per industry category are documented. The far right column depicts the *total* number of observations, and the *average* value for the other rows of information. The mean, standard deviation and the standard error of means are entered as percentages.

Table 4.5 Descriptive statistics on the interest rate per industry and year

		2005	***2006***	***2007***	***2008***	***2009***	***2010***	***2011***	***Total/ Average***
Frequency	**Primary**	313	303	330	295	347	330	301	2 219
	Oil/gas/mining	56	57	62	59	60	61	62	417
	Manufacturing	1 322	1 097	1 033	933	1 119	1 004	952	7 460
	Energy	77	75	89	100	111	116	116	684
	Construction	2 317	2 084	2 149	1 961	2 499	2 413	2 476	15 899
	Trade	4 128	3 607	3 564	3 271	3 835	3 495	3 428	25 328
	Shipping	59	52	60	57	56	48	56	388
	Travel	1 340	1 220	1 252	1 170	1 435	1 304	1 376	9 097
	Tele/IT	294	273	248	229	270	259	254	1 827
	Real estate	951	942	1 015	1 042	1 279	1 242	1 327	7 798
	Services	1 617	1 408	1 438	1 329	1 748	1 614	1 635	10 789
	Public/culture	1 005	940	1 035	993	1 198	1 130	1 198	7 499
	Mean	13479	12058	12275	11439	13957	13016	13181	89405
Mean (%)	**Primary**	6.102	6.180	7.116	9.051	7.441	6.619	6.462	6.991
	Oil/gas/mining	5.949	6.511	7.276	8.827	8.663	7.709	7.127	7.453
	Manufacturing	6.962	6.733	8.110	9.650	7.902	7.538	7.453	7.705
	Energy	6.012	5.995	7.115	8.605	6.167	5.912	5.499	6.454
	Construction	6.840	6.852	8.363	10.022	8.358	7.757	7.620	7.939
	Trade	7.345	7.205	8.292	10.046	8.439	7.880	7.979	8.132
	Shipping	5.716	6.204	7.039	8.520	6.562	6.725	6.472	6.754
	Travel	6.145	6.116	7.517	9.143	7.476	6.845	6.810	7.126
	Tele/IT	6.845	6.327	7.535	8.947	7.078	6.673	6.571	7.097
	Real estate	4.977	5.166	6.384	7.809	5.804	5.388	5.370	5.830
	Services	6.664	6.458	7.767	9.273	7.683	7.062	7.029	7.386
	Public/culture	5.889	5.733	6.945	8.492	7.136	6.609	6.656	6.790
	Mean	6.684	6.569	7.811	9.415	7.759	7.199	7.157	7.485

Table 4.5 Descriptive statistics on interest rate per industry and year, continues

		2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*Total/ Average*
Standard Deviation (%)	**Primary**	3.535	3.422	3.086	3.982	3.734	3.323	3.203	3.595
	Oil/gas/mining	2.974	2.891	3.555	3.597	3.623	3.842	3.485	3.558
	Manufacturing	3.717	3.539	3.902	4.399	3.946	3.949	3.765	3.975
	Energy	3.359	3.051	3.119	3.545	3.158	2.985	2.099	3.191
	Construction	3.701	3.629	3.835	4.307	4.023	3.779	3.730	3.976
	Trade	4.007	4.013	4.163	4.800	4.320	4.179	4.200	4.321
	Shipping	3.233	2.666	3.001	4.174	1.902	2.206	3.001	3.078
	Travel	3.104	3.079	3.387	3.788	3.521	3.316	3.195	3.472
	Tele/IT	3.849	3.626	3.928	4.354	4.023	4.250	4.248	4.104
	Real estate	2.661	2.536	2.762	3.160	2.608	2.523	2.380	2.798
	Services	3.747	3.679	3.935	4.285	4.149	3.748	3.809	4.000
	Public/culture	3.040	2.998	3.225	3.658	3.467	3.304	3.131	3.370
	Mean	3.695	3.614	3.809	4.310	3.973	3.783	3.726	3.940
Standard error (%)	**Primary**	0.130	0.143	0.146	0.148	0.132	0.138	0.130	0.052
	Oil/gas/mining	0.055	0.062	0.064	0.067	0.055	0.060	0.060	0.023
	Manufacturing	0.256	0.262	0.251	0.256	0.230	0.234	0.225	0.092
	Energy	0.065	0.072	0.077	0.087	0.075	0.082	0.081	0.029
	Construction	0.325	0.344	0.343	0.352	0.325	0.341	0.340	0.128
	Trade	0.397	0.417	0.410	0.423	0.378	0.388	0.382	0.151
	Shipping	0.057	0.060	0.063	0.066	0.054	0.053	0.057	0.022
	Travel	0.258	0.275	0.273	0.283	0.257	0.263	0.266	0.101
	Tele/IT	0.126	0.135	0.127	0.131	0.117	0.122	0.120	0.047
	Real estate	0.221	0.244	0.249	0.269	0.244	0.258	0.262	0.094
	Services	0.280	0.292	0.290	0.300	0.280	0.289	0.287	0.109
	Public/culture	0.226	0.244	0.251	0.263	0.237	0.247	0.250	0.093
	Mean	0.029	0.031	0.031	0.032	0.029	0.030	0.030	0.012

Within this control variable there are large differences in the frequencies of observations per category. There are few oil/gas/mining, energy and shipping companies involved. Most observations belong to trade, and then follow construction and services.

To understand the development of the describing numbers above more easily, look at figure 4.6 and figure 4.7. Figure 4.6 shows the interest rate averaged over all seven years, per industry code. To see the changes over time in more details, figure 4.7 is more suitable.

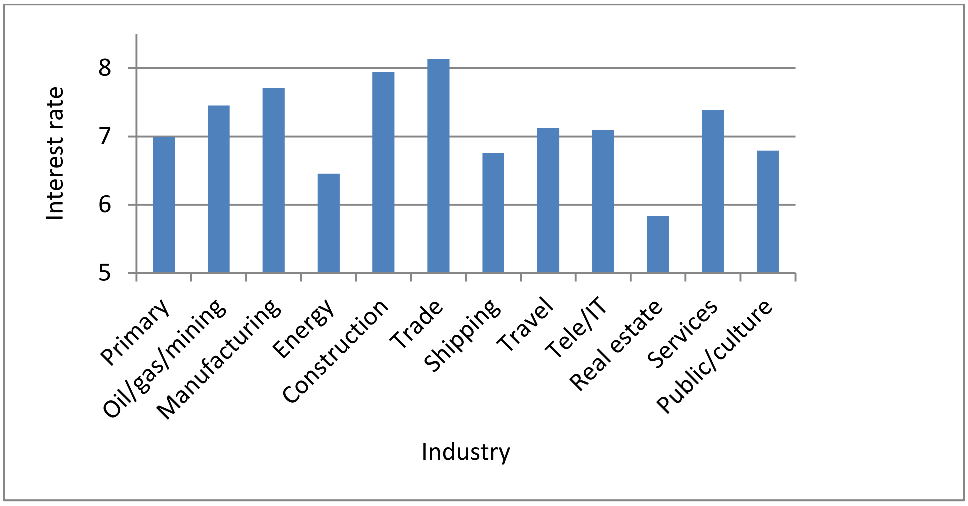

Figure 4.6 The interest rate per industry category

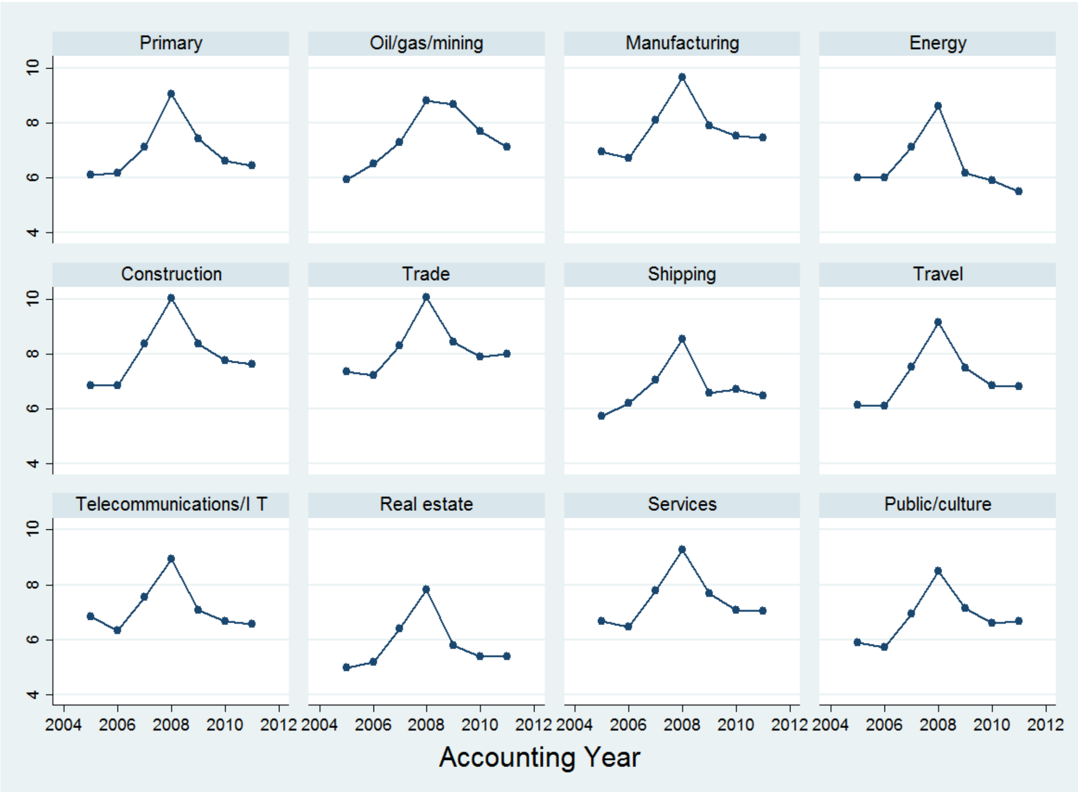

Figure 4.7 The interest rate per industry and year

It is quite evident that timing plays a large role in the level of interest rate per industry. The time patterns are similar and the average interest rate peaks in 2008. The lowest interest rate is mostly found in either 2005 or 2006. The exception is energy with the lowest average interest rate in 2011. For all years, real estate has the lowest interest rate, never above eight per cent and keeping steady around five per cent from 2009 to 2011. The highest average interest rate is held by trade, except for in 2007 and 2009 where construction-companies and oil/gas/mining-businesses had the highest average interest rates. The average interest rate of the oil/gas/mining industry does not have the same characteristic decline in interest rate in 2009.

Over time, the standard deviation and the standard error of means are highest for 2008. Regarding industries, the former is highest for trade, telecommunications and IT and services, whereas the latter is the highest for construction, trade and services –despite the fact that these industries have the highest frequencies.

After becoming more acquainted to the relevant variables, the next step is regression analysis.

4.2 Regression Analysis

In the previous section, various statistical *characteristics* of the variables were described. In this section, the statistical *significance* of the causal relationships between the dependent variable and the independent variables are tested, applying regression analysis. All models are multiple regression models. In model one the interest rate is analyzed on the basis of changes in the credit rating codes. In model two, age, size and the liquidity ratio compared are added as control variables. In model three, industry categories are added. When referring to the effect of one of the independent variables on the dependent variable, it is assumed that all other variables in the model are held constant.

Firstly, the regression assumptions are addressed.

4.2.1 Regression assumptions reviewed

It is important to review the model residuals in order to ensure the quality of the models. See section 3.9.1 for a definition of residuals. There are especially three assumptions regarding the residuals that should be held in order to induce trust towards the regression analysis results. These involve homoscedasticity, independency and normal distribution. The normal distribution test is executed last, in order to perform the test on the models *after* rectifying potential homoscedasticity and dependency. In addition, multicollinearity is addressed, a problem which may occur when having more than one explanatory variable.

The testing is documented for model one, with no control variables, and model three, with all control variables included. The results are assumed to apply to model two as well.

Homoscedasticity

Residuals should be homoscedastic. This means that the expected average value of the residuals is zero, i.e. that the residuals cancel each other out. If they are heteroscedastic, the variance around the regression line varies with the dependent variable, thus, the model's prediction ability varies with the value of the dependent variable.

In order to test for heteroskedasticity, the Breusch-Pagan test is applied. The results of the test for model one and three are documented in table 4.6.

Table 4.6 Breusch Pagan test of homoscedasticity, model one and three[18]

		2005	***2006***	***2007***	***2008***	***2009***	***2010***	***2011***
Model one	Chi^2	16.98	23.77	30.10	50.51	34.41	70.20	66.35
	p-value	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
Model three	Chi^2	241.01	285.65	143.60	271.42	443.53	504.21	646.76
	p-value	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005

In order not to reject the null hypothesis of homoscedasticity, the value of the chi-squared test of model one has to be below 9.49 at the five per cent significance level. The corresponding limit for model three is 28.87. All chi-squared values in table 4.6 are above these limits and all p-values are below five per cent. The null hypotheses are rejected each year, and the residuals cannot be said not to be heteroscedastic at the five per cent significance level. A solution is to run robust regressions. This means adjusting the standard errors, making them valid even when the form of the heteroscedasticity is unknown (Wooldridge, 2006). The coefficients' values and the R^2_{adj} do not change. This solution is especially suited for large samples, like the one in this report.

Independency

The residual should be independent and not correlated *with itself*. If this is not controlled for, the standard errors become too small. This is especially present for panel data, i.e. data over more than one time period. Regarding time, the problem is called autocorrelation. In this thesis, each year is analyzed separately in order to remove this risk of autocorrelation.

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[18] The significance level is never zero, thus entered as 0.0005.

Independency can also be a problem within groups of units. For example, two companies with the same rating code can have more similar characteristics than two companies with different rating codes. A solution is to use dummy variables. The variation *between* groups is held constant and the focus is on the variances *within* the group. These are applied to the credit rating codes and the industry categories. Clustering the panel variables is also done for the same reason (Midtbø, 2012). The panel variables used for clustering are the organization numbers.

Normal distribution

The residuals should be normally distributed so that the chance of under- and over-estimating a value is about the same (Midtbø, 2012). The residuals' distributions after running robust regressions with clustered panel data are illustrated in figure 4.8 and figure 4.9. Normal distribution is bell curved. The X-axis shows the interest rate and the height of the histograms shows the density. From looking at figure 4.8, the residuals seem *approximately* normally distributed. See attachment 7.3 and 7.4 to see the residuals plotted against a normal distribution in q-q-plots.

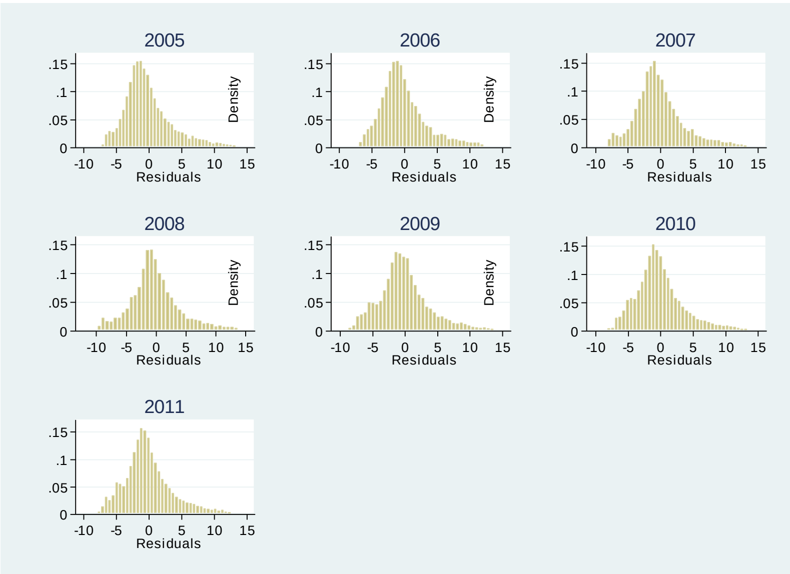

Figure 4.8 The distribution of residuals, model one

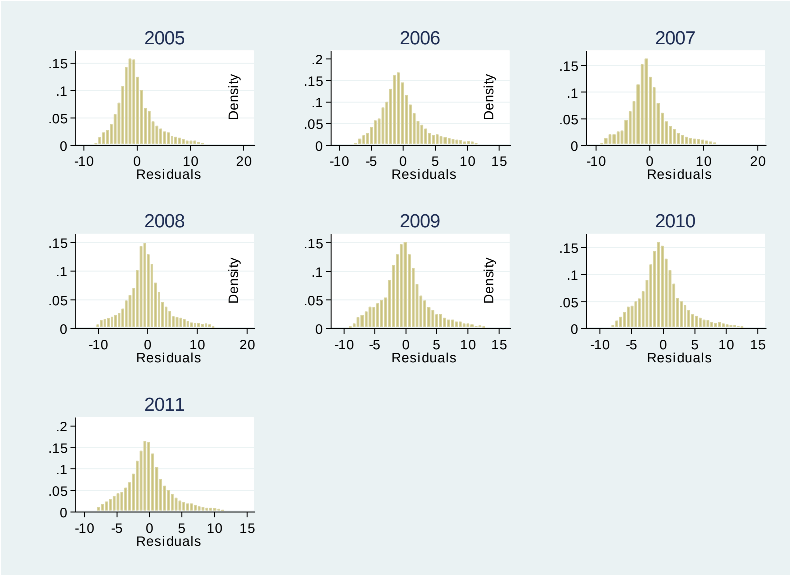

Figure 4.9 The distribution of residuals, model three

In order to test the distribution more accurately, a skewness and kurtosis test called the Kolmogorov-Smirnov test is performed. The results of the test are documented in table 4.7.

Table 4.7 Kolmogorov-Smirnov test of normal distribution, model one and three[19]

		2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*
Model one	Combined K-S	0.0995	0.0947	0.0823	0.0767	0.0736	0.0782	0.0810
	p-value	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
Model three	Combined K-S	0.0948	0.0912	0.0822	0.0807	0.0726	0.0762	0.0772
	p-value	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005

The Kolmogorov-Smirnov test tests if data is of a specific distribution. In this case, the distribution of the residuals of the models is tested against the *normal* distribution. The null hypothesis of normality is rejected as the p-value for all years is below five per cent. In order to achieve normally distributed residuals, the residuals may be *transformed*. The residuals were tested for several types of transformations and the results from the test run on the 2005-values can be seen in figure 4.10 and figure 4.11 as well as in table 4.8. The diagram named *identity* is the current state of the residuals' distribution.

[19] The significance level is never zero, thus entered as 0.0005.

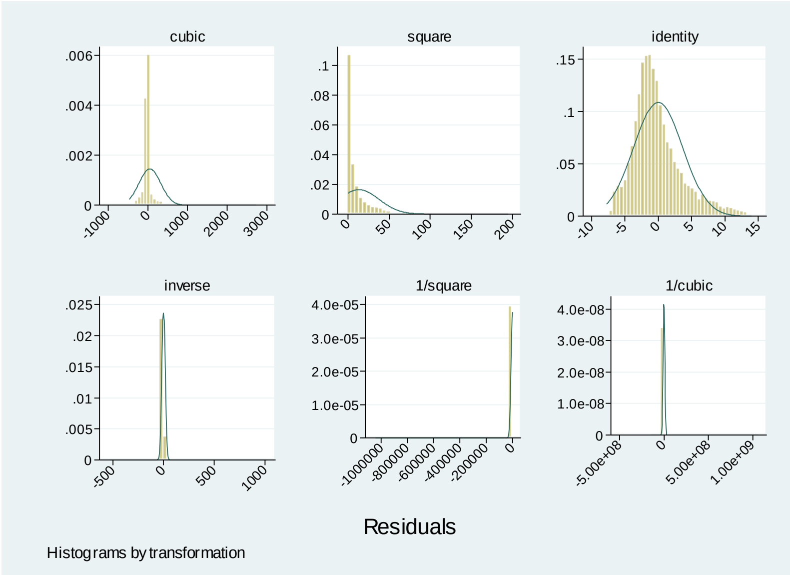

Figure 4.10 Transformation attempts on residuals, model one in 2005

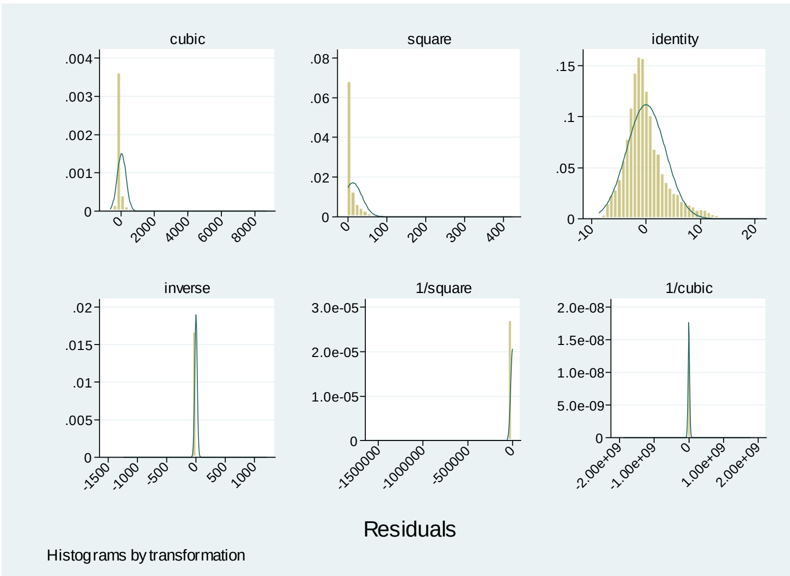

Figure 4.11 Transformation attempts on residuals, model three in 2005

The current distributions seem to be the one closest to a normal distribution.

Table 4.8 Transformation attempts on residuals, model one and three in 2005

	Formula	***chi***^{2}	***p-value***
cubic	residual^3	.	.
square	residual^2	.	.
identity	residual	.	.
square root	square root(residual)	.	.
log	log(residual)	.	.
1/(square root)	1/square root(residual)	.	.
inverse	1/residual	.	.
1/square	1/(residual^2)	.	.
1/cubic	1/(residual^3)	.	.

In table 4.8, the null-hypothesis is that the transformation does not apply. If the p-value had been above five per cent, the data would have been transformed. In table 4.8, it is evident that none of the transformations would lead to more normally distributed residuals. The calculations above are gathered from testing the residuals from the regression analyses in 2005. The same results apply to all years. As normality tests are very sensitive to deviations from the normal distribution when the sample is large (Midtbø, 2012), normality is still assumed. The regression results are assumed to be reliable.

Multicollinearity

Multicollinearity can occur when a regression model contains several explanatory variables and at least two of them are correlated with each other. One example is when the number of dummy variables equals the number of groups represented. To avoid this, one reference category is always taken out when entering credit rating codes and industry categories into the regression. The rating code AAA and the real estate industry are chosen to be omitted. If not selected manually, Stata, nevertheless, automatically omits one of the categories in order to avoid multicollinearity. Models with a large R^2_{adj} often have problems with multicollinearity (Midtbø, 2012). The regression models presented in section 5.2 do not have large R^2_{adj}.

High multicollinearity does not violate the assumption, but *perfect* multicollinearity does (Midtbø, 2012). Model one and three are tested using the variation inflation factor test. A rule of thumb is that a value below ten is not considered a problem (Midtbø, 2012). The test is taken on robust regressions controlled for clusters within organization numbers and the results can be seen in table 4.9 and table 4.10.

Table 4.9. Variation inflation factor test of multicollinearity, model one

	2005	***2006***	***2007***	***2008***	***2009***	***2010***	***2011***
C	1.06	1.03	1.05	1.06	1.11	1.08	1.10
B	1.73	1.51	1.45	1.57	1.89	1.76	1.62
A	2.36	2.07	1.91	2.14	2.30	2.21	2.02
AA	2.48	2.16	2.01	2.23	2.46	2.35	2.17
Average VIF	1.91	1.69	1.61	1.75	1.94	1.85	1.73

Table 4.10 Variation inflation factor test of multicollinearity, model three

	2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*
C	1.06	1.04	1.06	1.07	1.12	1.09	1.11
B	1.79	1.58	1.53	1.65	1.97	1.84	1.68
A	2.45	2.19	2.04	2.29	2.41	2.31	2.11
AA	2.50	2.18	2.04	2.26	2.48	2.37	2.18
Primary	1.31	1.30	1.30	1.26	1.25	1.24	1.21
Oil/gas/mining	1.06	1.06	1.06	1.06	1.04	1.05	1.05
Manufacturing	2.19	2.01	1.89	1.78	1.76	1.70	1.63
Energy	1.08	1.08	1.08	1.09	1.08	1.09	1.08
Construction	2.94	2.75	2.67	2.49	2.50	2.47	2.73
Trade	3.82	3.47	3.30	3.07	3.02	2.90	2.67
Shipping	1.06	1.05	1.06	1.05	1.04	1.04	1.04
Travel	2.22	2.12	2.06	1.96	1.95	1.89	1.87
Tele/IT	1.29	1.28	1.24	1.21	1.20	1.19	1.18
Real Estate	2.47	2.28	2.22	2.10	2.15	2.01	2.04
Services	1.97	1.90	1.92	1.85	1.84	1.81	1.80
Size	1.07	1.08	1.09	1.09	1.10	1.10	1.10
Age	1.04	1.05	1.06	1.07	1.06	1.06	1.05
Liquidity compared	1.00	1.00	1.01	1.00	1.00	1.01	1.00
Average VIF	1.79	1.69	1.65	1.63	1.67	1.62	1.57

The values are well below ten, indicating no problems concerning multicollinearity in the sample.

Briefly summarized, robust regressions are run to make the standard error of means valid, each year is analyzed separately to avoid autocorrelation, and dummy variables and clustering of organization numbers are implemented to avoid dependency. All these applications lead to more trustworthy regression analyses.

In the following sections, the regression results are *described*. In section five, they are *discussed*. Technical terms are explained in section 3.9.1, but also often repeated in the following sections whilst put into context.

4.2.2 Model one

The first regression executed is called model one. The independent variables are the credit rating codes. The AAA-rating code is the reference dummy. The null hypothesis is that all coefficients belonging to the credit rating codes are equal to zero, i.e. have no effect on the interest rate.

The model is documented in table 4.11. The top value for each variable is the coefficient, the second value is the robust standard error of means and the third value is the t-value. The two former values together with the R^2_{adj} are entered as percentages.

Table 4.11 Regression analysis, model one

	2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*
C vs. AAA	1.868***	3.441***	2.611***	3.526***	3.003***	3.181***	2.751***
	0.391	0.537	0.409	0.498	0.307	0.379	0.297
	4.775	6.406	6.379	7.077	9.79	8.382	9.255
B vs. AAA	1.391***	1.582***	1.483***	1.624***	1.838***	1.531***	1.390***
	0.126	0.134	0.138	0.164	0.125	0.125	0.122
	11.032	11.775	10.771	9.896	14.682	12.234	11.398
A vs. AAA	0.783***	0.979***	0.677***	0.595***	0.754***	0.425***	0.350***
	0.103	0.099	0.102	0.124	0.109	0.104	0.099
	7.589	9.845	6.663	4.794	6.928	4.097	3.55
AA vs. AAA	0.390***	0.609***	0.510***	0.347**	0.509***	0.164*	0.188**
	0.098	0.095	0.095	0.119	0.103	0.098	0.091
	3.986	6.436	5.363	2.915	4.933	1.681	2.071
Constant (AAA)	6.084***	5.819***	7.215***	8.859***	6.988***	6.744***	6.745***
	0.085	0.081	0.079	0.102	0.089	0.084	0.077
	71.209	72.164	90.79	86.65	78.082	80.299	87.929
F-value	40.57	48.77	36.86	36.74	76.39	62.62	55.46
R^2_{adj}	1.202	1.727	1.281	1.557	2.325	2.245	1.964
Frequency	13 479	12 058	12 275	11 439	13 957	13 016	13 181

*Note: The stars denote the p-values, *** p<0.01, ** p<0.05, * p<0.1.*

With a degree of freedom-numerator at four and a denominator at ∞, the F-value is above 2.37 and is thus sufficiently large to reject the null hypothesis each year. The difference is significantly different from zero at the five per cent significance level, each year. This indicates that the interest rate of AAA-rated companies is different from the interest rate of at least *one* other rating code.

The coefficients of the non-omitted parameters describe the *difference* between the average interest rate of each credit rating code and the average interest rate of AAA-rated companies. The coefficients are positive, thus describing how much *higher* the average interest rates for AA-, A-, B- and C-rated companies are compared to AAA-rated companies.

For 2005 the regression formula appears like equation 4.1.

$$Y = 6.084 + 1.868 * C + 1.391 * B + 0.783 + A + 0.390 * AA \qquad \text{Equation 4.1}$$

The intercept, 6.084 per cent, being the interest rate of an AAA-rated company, is also found in table 4.2 in the descriptive analysis. If a company has a B-rating, B is one and the other rating codes are zero (referring to the treatment of dummy variables). The average interest rate would, according to the regression equation, be 6.084 per cent + 1.391 per cent * 1 = 7.475 per cent. This value is also found in table 4.2.

Almost all t-values, describing the significance of each parameter, are above 1.96 and so these results are statistically significant at the five per cent significance level. The p-values below five per cent indicate the same[20]. There is thus a five (or less) per cent chance that the average interest rates belonging to different rating codes indeed are similar (that the null hypothesis is falsely rejected). One exception is found in 2010, where the interest rate of AA-rated companies was only significantly different from the interest rate of AAA-rated companies at a ten per cent significance level (grey area in table 4.11).

When only looking at the value of the coefficients of the credit rating codes, the largest difference is found between C- and AAA-rated companies in 2008. The difference is 3.526 per cent. However, when considering the standard error as well, it is evident that there is a greater uncertainty around this difference than, for example, the difference between B-rated and AAA-rated companies in 2009, where the t-value is double the size compared to the former example. The larger the t-value is, the smaller is the standard error relative to the value of the coefficient. The largest robust standard errors of means belong to the C-rated companies[21] and the largest robust standard errors *relative* to the value of their coefficient belong to rating code AA- and A-rated companies. The largest t-values are held by B-rated companies each year, due to the combination of large coefficients and low robust standard error of means.

The credit rating codes are categorical and the AAA-rating is the omitted variable. This means that when all parameters included in the model (C, B, A, AA) are zero, the company in question is AAA-rated and the constant thus depicts the interest rate of an AAA-rated company (it therefore says “(AAA)” below the constant in table 4.11).

When applying table 4.11 it is possible to read off the difference between *each* pair of rating codes by looking at the deviation between the values of their coefficients. However, the

[20] Most of the p-values imply that the differences between the average interest rates of AAA-rated companies and companies rated otherwise are statistically different from zero at the *one* per cent significance level –but the focus in this thesis is mainly kept on the five per cent significance level, unless otherwise stated.

[21] In this case, “the C-rated companies” refers to the average interest rate difference between C- and AAA-rated companies. Such abbreviations are applied throughout the thesis for reader friendliness.

significance of these differences is not available for interpretation. As the significance of the difference between *each* pair of credit rating codes is of interest, an additional analysis has been documented in table 4.12. The left column depicts the remaining credit rating codes being compared. The top value for each comparison is the coefficient, the second value is the robust standard error of means and the third value is the t-value. The two former values are entered as percentages.

Table 4.12 Interest rate differences from credit rating code B to AA, model one

	2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*
C vs. B	0.477	1.858***	1.128***	1.901***	1.165***	1.650***	1.361***
	0.393	0.542	0.417	0.504	0.306	0.382	0.302
	1.21	3.43	2.71	3.77	3.80	4.32	4.50
C vs. A	1.085***	2.461***	1.934***	2.931***	2.249***	2.755***	2.401***
	0.386	0.534	0.406	0.493	0.300	0.375	0.294
	2.81	4.61	4.76	5.95	7.50	7.35	8.17
C vs. AA	1.478***	2.831***	2.101***	3.179***	2.494***	3.017***	2.563***
	0.385	0.533	0.405	0.491	0.298	0.373	0.291
	3.84	5.31	5.19	6.47	8.37	8.08	8.80
B vs. A	0.608***	0.603***	0.806***	1.030***	1.084***	1.106***	1.040***
	0.110	0.122	0.129	0.146	0.107	0.111	0.113
	5.57	4.93	6.24	7.03	10.12	9.95	9.19
B vs. AA	1.001***	0.973***	0.973***	1.277***	1.329***	1.367***	1.202***
	0.104	0.118	0.124	0.142	0.101	0.105	0.107
	9.61	8.22	7.85	8.98	13.11	12.99	11.28
A vs. AA	0.393***	0.370***	0.167**	0.248***	0.245***	0.261***	0.162**
	0.075	0.077	0.082	0.093	0.080	0.079	0.079
	5.25	4.83	2.04	2.66	3.05	3.32	2.06

*Note: The stars denote the p-values, *** p<0.01, ** p<0.05, * p<0.1.*

Most differences are quite large in size. Even though some of the average interest rate differences between A-rated and AA-rated companies are small, the standard errors of means are so too, thus making small differences significant. From table 4.12 only the difference between C- and B-rated companies in 2005 is not statistically significant at the five per cent significance level (grey area).

4.2.3 Model two

When creating model two, the control variables size, year of incorporation and liquidity ratio compared are added to the regression in order to understand how they influence the interest rate. Size is represented by the sum of assets and divided by 100. This means that the interpretation is *the interest rate change if a company increase or decreases its size with NOK 100 000* (since the numbers in the data are already in thousands as well). This is done as a change of NOK 1 000 is too small to expect any noticeable interest rate changes. The results are shown in table 4.13.

Again, the top value for each variable in the table is the coefficient, the second value is the robust standard error of means and the third value is the t-value. The two former values together with the R^2_{adj} are entered as percentages.

Table 4.13 Regression analysis, model two

	2005	***2006***	***2007***	***2008***	***2009***	***2010***	***2011***
C vs. AAA	1.772***	3.261***	2.390***	3.267***	2.703***	2.845***	2.479***
	0.393	0.533	0.406	0.500	0.310	0.375	0.301
	4.510	6.118	5.889	6.541	8.708	7.587	8.231
B vs. AAA	1.099***	1.320***	1.212***	1.332***	1.462***	1.141***	1.048***
	0.126	0.135	0.139	0.167	0.126	0.126	0.122
	8.714	9.753	8.703	7.985	11.587	9.046	8.595
A vs. AAA	0.626***	0.798***	0.516***	0.402***	0.486***	0.160	0.082
	0.103	0.100	0.103	0.125	0.109	0.104	0.099
	6.094	7.945	5.013	3.201	4.452	1.543	0.827
AA vs. AAA	0.324***	0.529***	0.413***	0.246**	0.386***	0.024	0.088
	0.097	0.094	0.095	0.119	0.102	0.096	0.089
	3.351	5.623	4.370	2.075	3.780	0.252	0.978
Size (100 000)	-0.037***	-0.028***	-0.024***	-0.025***	-0.035***	-0.034***	-0.034***
	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	-17.904	-14.801	-12.512	-12.140	-18.122	-19.721	-20.737
Year of incorp.	-0.012***	-0.006*	-0.005	0.003	0.003	-0.000	-0.004
	0.003	0.003	0.003	0.004	0.003	0.003	0.003
	-3.590	-1.765	-1.348	0.652	0.946	-0.046	-1.191
Liq. ratio compared	-0.183***	-0.038**	-0.087**	-0.038*	-0.016*	-0.030***	-0.024***
	0.048	0.016	0.035	0.020	0.009	0.011	0.007
	-3.852	-2.317	-2.450	-1.868	-1.850	-2.732	-3.684
Constant (AAA)	30.606***	18.277***	17.387**	4.469	1.823	8.122	15.239**
	6.537	6.601	6.961	7.989	6.578	6.420	6.245
	4.682	2.769	2.498	0.559	0.277	1.265	2.440
F-value	72.92	60.39	45.29	44.89	96.03	96.61	99.28
R^2_{adj}	4.121	3.575	3.011	2.890	4.547	4.901	4.747
Frequency	13 470	12 051	12 265	11 431	13 947	13 002	13 165

*Note: The stars denote the p-values, *** p<0.01, ** p<0.05, * p<0.1.*

In order to reject the null hypothesis that none of the variables significantly influence the interest rate, the F-value has to be above 2.01 (calculated using degrees of freedom equal to 7 and ∞). As all F-values are above this threshold, there is a 95 per cent chance that at least one of the coefficients is not equal to zero, each year. The results for each variable are presented below in the same order as in the table.

As in model one, the signs of the credit rating codes' coefficients are positive, indicating that the non-omitted rating codes possess higher interest rates than the reference rate AAA. The order of the size of the coefficients of the rating codes is also as in model one. Also, again, the interest rate of C-rated companies is larger than the interest rate of B-rated companies, which again is larger than the interest rate of A-rated companies etc.

The values of the coefficients decreased compared to model one, leading to three changes of statistical significance. The largest decrease in the value of the coefficients occurred between A- and AAA-rated companies, decreasing above 0.260 per cent both in 2010 and in 2011. This led to insignificant differences these years. The same applies to the interest rate difference between AA-rated and AAA-rated companies in 2011. These observations are colored grey in table 4.13, carrying t-values below the relevant threshold of 1.96. The interval, within which the average value lies, contains zero as a potential value (the interval being +/- two standard errors on both sides of the value of the coefficient).

The significance regarding the difference between the remaining rating codes is displayed in table 4.14. The top value for each comparison is the coefficient, the second value is the robust standard error of means and the third value is the t-value. The two former values are entered as percentages.

Table 4.14 Interest rate differences from credit rating code B to AA, model two

	2005	***2006***	***2007***	***2008***	***2009***	***2010***	***2011***
C vs B	0.673*	1.941***	1.178***	1.940	1.241***	1.704***	1.431***
	0.394	0.538	0.413	0.505	0.309	0.370	0.305
	1.71	3.61	2.86	3.83	4.02	4.52	4.69
C vs A	1.146***	2.463***	1.874***	2.866	2.218***	2.685***	2.397***
	0.387	0.530	0.402	0.493	0.302	0.370	0.297
	2.96	4.65	4.66	5.83	7.33	7.25	8.07
C vs AA	1.448***	2.731***	1.977***	3.021	2.318***	2.821***	2.391***
	3.89	0.529	0.401	0.492	0.301	0.369	0.295
	3.75	5.16	4.93	6.14	7.69	7.65	8.10
B vs A	0.473***	0.522***	0.700***	0.934	0.976***	0.981***	0.966***
	0.108	0.121	0.129	0.146	0.107	0.111	0.112
	4.39	4.30	5.41	6.36	9.17	8.87	8.62
B vs AA	0.776***	0.790	0.799***	1.086	1.076***	1.116***	0.960***
	0.104	0.119***	0.124	0.144	0.102	0.106	0.106
	7.45	6.66	6.43	7.56	10.57	10.56	9.02
A vs AA	0.302***	0.268***	0.103	0.155*	0.100	0.136*	-0.006
	0.074	0.077	0.0082	0.094	0.080	0.078	0.079
	4.06	3.49	1.25	1.66	1.24	1.73	-0.07

*Note: The stars denote the p-values, *** p<0.01, ** p<0.05, * p<0.1.*

The interest rate difference between C-rated and B-rated companies in 2005 is statistically significant at the ten per cent level, but not at the five per cent significance level[22]. From

[22] In model one, this difference was not even significant at the ten per cent level.

2007 to 2011 the interest rate differences between A-rated and AA-rated companies are now deemed insignificant at the five per cent significance level. Their t-values in model one were just above the threshold. In model two, the values of the coefficients decreased, reducing the t-values to a level just *below* the threshold, making their interest rate differences insignificant.

A company's size is a significant factor for all years. The t-values are large compared to the t-values of the credit rating codes due to relatively low standard errors compared to the value of the coefficients. The coefficients are negative, indicating an inverse relationship between size and the interest rate. Larger firms have more favorable interest rates than smaller firms.

The number of years since incorporation is a significant parameter only in 2005. In this year, the coefficient's sign is negative, indicating that older companies have *higher* interest rates than younger companies. From 2006 to 2011, no statistically significant linear dependency between the mean interest rate and the year of incorporation was detected.

The liquidity ratio is statistically significant in 2005, 2006, 2007, 2010 and 2011. The signs of the significant liquidity ratio compared coefficients are negative, implying that the larger a company's liquidity ratio compared is, the lower the interest rate is. However, the t-values are low, indicating low significance of this variable compared to the other significant results.

The constant still represents the value of the interest rate when all parameters are zero, i.e. the interest rate of an AAA-rated company, now also controlled for size, the year of incorporation and the liquidity ratio compared. However, these three latter parameters are never zero simultaneously[23]. Also, the constant is insignificant from 2008 to 2010.

4.2.4 Model three

Model three was created in order to understand how industry affiliation influences the interest rate of a company. Industry is a categorical variable and the real estate industry is chosen as the reference dummy. The results are shown in table 4.15.

[23] Only the liquidity ratio compared can be zero; this occurred in only seven observations.

Again, the top value for each variable in the table is the coefficient, the second value is the robust standard error of means and the third value is the t-value. The two former values together with the R^2_{adj} are entered as percentages.

Table 4.15 Regression analysis, model three

	2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
C vs. AAA	1.757*** 0.389 4.513	3.220*** 0.524 6.146	2.491*** 0.396 6.294	3.363*** 0.499 6.742	2.727*** 0.311 8.765	2.810*** 0.378 7.438	2.450*** 0.296 8.274
B vs. AAA	1.055*** 0.126 8.393	1.351*** 0.136 9.957	1.322*** 0.139 9.479	1.436*** 0.167 8.616	1.602*** 0.125 12.804	1.225*** 0.125 9.801	1.158*** 0.120 9.643
A vs. AAA	0.692*** 0.104 6.670	0.896*** 0.102 8.753	0.726*** 0.105 6.948	0.665*** 0.128 5.191	0.781*** 0.110 7.115	0.393*** 0.104 3.774	0.365*** 0.099 3.690
AA vs. AAA	0.279*** 0.097 2.880	0.528*** 0.095 5.575	0.489*** 0.095 5.160	0.336*** 0.120 2.806	0.494*** 0.102 4.844	0.086 0.096 0.895	0.141 0.088 1.593
Size (100 000)	-0.035*** 0.002 -16.772	-0.027*** 0.002 -14.081	-0.023*** 0.002 -11.519	-0.023*** 0.002 -11.005	-0.031*** 0.002 -16.082	-0.031*** 0.002 -17.811	-0.029*** 0.002 -17.918
Age	-0.008** 0.003 -2.431	-0.002 0.003 -0.682	-0.002 0.003 -0.658	0.004 0.004 1.117	0.003 0.003 1.044	0.002 0.003 0.594	-0.001 0.003 -0.263
Liq. ratio compared	-0.183*** 0.047 -3.940	-0.038** 0.016 -2.338	-0.087** 0.038 -2.307	-0.038* 0.022 -1.700	-0.016* 0.008 -1.951	-0.031*** 0.011 -2.880	-0.025*** 0.008 -3.172
Primary	1.178*** 0.219 5.384	1.050*** 0.211 4.973	0.765*** 0.191 4.001	1.286*** 0.251 5.133	1.583*** 0.214 7.410	1.154*** 0.192 6.003	1.002*** 0.192 5.213
Oil/gas/mining	1.160*** 0.399 2.910	1.781*** 0.365 4.877	1.014** 0.453 2.238	1.188** 0.477 2.488	2.988*** 0.418 7.154	2.437*** 0.452 5.385	1.987*** 0.426 4.667
Manufacturing	1.980*** 0.133 14.860	1.647*** 0.137 12.008	1.767*** 0.152 11.651	1.835*** 0.174 10.527	2.063*** 0.137 15.010	2.052*** 0.142 14.467	1.988*** 0.137 14.516

Table 4.15 Regression analysis, model three continues

	2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*
Energy	0.963**	0.809**	0.702**	0.844**	0.470	0.596**	0.180
	0.380	0.361	0.342	0.365	0.305	0.283	0.198
	2.533	2.243	2.049	2.311	1.543	2.106	0.908
Construction	1.888***	1.794***	2.057***	2.265***	2.515***	2.271***	2.161***
	0.118	0.120	0.125	0.142	0.110	0.107	0.102
	16.043	14.970	16.472	15.955	22.855	21.178	21.232
Trade	2.236***	1.937***	1.797***	2.085***	2.434***	2.257***	2.355***
	0.108	0.109	0.115	0.131	0.102	0.101	0.099
	20.768	17.785	15.606	15.940	23.824	22.258	23.870
Shipping	0.816*	1.169***	0.774*	0.673	1.000***	1.544***	1.227***
	0.425	0.371	0.397	0.572	0.273	0.357	0.409
	1.919	3.152	1.951	1.178	3.656	4.329	3.002
Tele/IT	1.104***	0.929***	1.129***	1.252***	1.538***	1.284***	1.279***
	0.121	0.123	0.132	0.149	0.117	0.116	0.109
	9.135	7.558	8.549	8.411	13.148	11.067	11.743
Travel	1.681***	1.025***	0.999***	0.889***	1.044***	0.974***	0.948***
	0.239	0.236	0.264	0.301	0.255	0.269	0.270
	7.048	4.351	3.788	2.951	4.094	3.623	3.511
Services	1.528***	1.180***	1.289***	1.334***	1.652***	1.434***	1.402***
	0.128	0.132	0.139	0.157	0.124	0.118	0.116
	11.898	8.970	9.246	8.492	13.313	12.111	12.086
Public	0.785***	0.463***	0.449***	0.530***	1.105***	0.993***	1.025***
	0.131	0.132	0.136	0.154	0.125	0.123	0.113
	5.977	3.509	3.298	3.436	8.842	8.108	9.088
Constant (AAA and real estate)	21.116***	9.705	11.052	-0.994	-0.786	2.260	7.557
	6.433	6.605	6.965	8.012	6.477	6.282	6.056
	3.283	1.469	1.587	-0.124	-0.121	0.360	1.248
F-value	61.69	46.96	40.68	40.86	82.92	78.08	85.75
R^2_{adj}	7.057	6.345	5.636	5.540	8.143	8.441	8.558
Frequency	13 470	12 051	12 265	11 431	13 947	13 002	13 165

*Note: The stars denote the p-values, *** p<0.01, ** p<0.05, * p<0.1.*

The F-values are all above the threshold of 1.83 (calculated using degrees of freedom equal to 18 and ∞). There is thus a 95 per cent chance that at least one of the coefficients are not equal to zero, each year.

When moving from model two to model three, the signs of the coefficients of the credit rating codes as well as the order of the size of the coefficients are the same. Regarding the significance, almost all t-values of the credit rating codes *increased*[24]. The interest rate differences between A-rated and AAA-rated companies in 2010 and 2011 are again significant, as in model one.

The significance regarding the difference between the remaining rating codes is displayed in table 4.16. The top value for each comparison is the coefficient, the second value is the robust standard error of means and the third value is the t-value. The two former values are entered as percentages.

Table 4.16 Interest rate differences from credit rating code B to AA, model three

	2005	***2006***	***2007***	***2008***	***2009***	***2010***	***2011***
C vs. B	0.702* 0.390 1.80	1.869*** 0.529 3.54	1.169*** 0.402 2.91	1.927*** 0.504 3.82	1.125*** 0.308 3.65	1.585*** 0.380 4.18	1.292*** 0.300 4.31
C vs. A	1.065*** 0.383 2.78	2.325*** 0.521 4.46	1.770*** 0.391 4.51	2.698*** 0.493 5.47	1.946*** 0.303 6.43	2.420*** 0.373 6.47	2.085*** 0.293 7.13
C vs. AA	1.478*** 0.382 3.87	2.692*** 0.520 5.18	2.002*** 0.390 5.13	3.028*** 0.492 6.16	2.234*** 0.302 7.41	2.724*** 0.372 7.33	2.309*** 0.290 7.96
B vs. A	0.363*** 0.106 3.42	0.456*** 0.120 3.80	0.596*** 0.127 4.70	0.771*** 0.144 5.37	0.821*** 0.104 7.88	0.831*** 0.108 7.68	0.793*** 0.110 7.23
B vs. AA	0.776*** 0.103 7.56	0.822*** 0.117 7.00	0.833*** 0.123 6.76	1.100*** 0.141 7.78	1.109*** 0.100 11.11	1.139*** 0.104 10.96	1.016*** 0.104 9.75
A vs. AA	0.413*** 0.074 5.58	0.367*** 0.077 4.80	0.237*** 0.082 2.88	0.329*** 0.093 3.54	0.288*** 0.079 3.62	0.309*** 0.078 3.94	0.224*** 0.078 2.86

*Note: The stars denote the p-values, *** p<0.01, ** p<0.05, * p<0.1.*

The difference between C- and B-rated companies in 2005 is statistically significant at the ten per cent significance level, but not at the five per cent level. This coincides with the results in model two. The interest rate differences between A-rated and AA-rated companies from 2007 to 2011 are yet again significant.

The statistical significance of a company's size, year of incorporation and liquidity ratio compared is the same as in model two. Size is significant for all years, the year of incorporation is only significant in 2005 and the liquidity ratio compared is insignificant in

[24] Most of the time the increase was caused by larger coefficients, and sometimes it was caused by smaller standard error of means, or the combination of both.

2008 and 2009. The relationships these three variables have to the interest rate are still inverse.

The coefficients of the industry categories depict how much the average interest rates differ due to their industry affiliation, given that all other parameters are kept constant. The chosen reference dummy could have been any industry, but the real estate industry was chosen in order to ease the interpretation of the results. As real estate companies have the lowest average interest rate each year, all coefficients have the same sign; positive. The standard errors of means of the industries show the interest rate variations *within* the relevant industry category. This is because the variations *between* industries are kept constant through allowing dummy variables to represent the industries in the model.

The interest rate differences among industries are statistically significant at a five per cent significance level for the observations that are not colored grey in table 4.15. The grey areas consist of companies affiliated with the energy industry in 2009 and 2011 and the shipping industry in 2005, 2007 and 2008. It is the combination of low coefficient values and relatively high standard errors that makes these observations insignificant. From the coefficients it is clear that trade, construction, manufacturing and oil/gas/mining are the industries that contribute with the highest interest rates compared to real estate's interest rate, and thus also overall, as was depicted in figure 4.6 in the descriptive analysis.

When entering *two* dummy variables, one for the credit rating codes and one for the industries, there are two dimensions to consider when interpreting the constant. Now, when the coefficients of all the included variables are zero, the constant term depicts the interest rate of an AAA-rated *real estate* company. However, again, the parameters included in the model are never zero simultaneously and the constants are not paid attention to. It is also insignificant in six out of seven years.

4.2.5 The coefficient of determination

The coefficient of determination is not emphasized in this thesis, as a focus around the significance of each variable has been preferred. Nevertheless, the development is illustrated in figure 4.12.

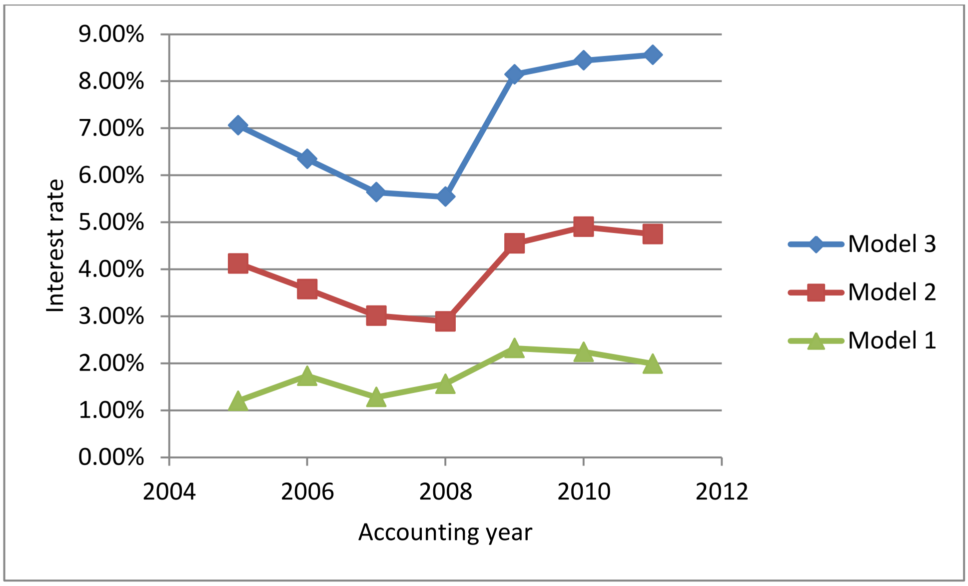

Figure 4.12 The coefficient of determination

Model one has an R^2_{adj} spanning from 1.202 per cent to 2.245 per cent. When adding control variables in model two, the explanatory power decreases steadily towards 2008, before it increases. Model two has an R^2_{adj} between 2.890 per cent to 4.901 per cent. When including the industry variables, the explanatory power follows the same pattern as in model two, however, with an increased R^2_{adj} from 5.540 per cent to 8.558 per cent[25].

Based on the results, the credit rating codes, the size, the liquidity ratios compared and the industry categories contribute to explain the variations in the interest rate to different degrees. The influence of the credit rating codes on the interest rates is seemingly *robust*, as the results for these variables do not change much when control variables are added. The preciseness of the calculation of the codes' effect on a company's average interest rate is thus also verified.

[25] The numbers are the minimum and maximum values, not the values in 2005 and 2011.

5. Discussion, implications and conclusion

The results are put into context and discussed before the implications of the report are addressed. The second sub-section includes suggestions for further research. The conclusion completes the thesis.

5.1 Discussion

One of the questions mentioned in the introduction was *what is an interest rate*? -and in short, it has been established that it is the price of money. The calculation of the price of money depends on the second sub-question *what is creditworthiness*? Creditworthiness is the calculation of the probability of repayment of credit principals and interest costs. The level of worthiness is attributed to companies by applying credit rating codes. These cover a broad area of parameters in order to portray a most accurate picture of the relevant credit risk within one single symbol. The hypothesis in this thesis is that the interest rate decreases when creditworthiness increases. The following discussion confirms this hypothesis.

The regression results of each variable are discussed separately. Supplementary information derived from the descriptive statistics is added where appropriate. Economic significance is also addressed simultaneously. This creates a clear disposition.

The causality between the dependent variable and the independent variables was reviewed applying three multiple regression models. In all models the average interest rates of the credit rating codes lay in the expected order each year. Companies rated C pay relatively higher interests than companies rated B and these again pay relatively higher interests than companies rated A etc. The expectation of the order is caused by the assumption of risk aversion. Higher risk entails a requirement of higher compensation.

In model one, only two results were insignificant. When moving from model one to model two, eight additional credit rating results are insignificant[26]. This was caused by the fact that some of the effects previously captured by the credit rating codes are now being captured by the added control variables. While the standard errors stayed almost constant, the

[26] When considering the statistical significance level at five per cent.

coefficients decreased. The insignificance includes differences between A- and AAA-rated companies, AA- and AAA- rated companies and A- and AA-rated companies. This indicates that the creditors do not punish companies much for a downgraded credit rating code if they at least hold a rating containing an “A”.

In model three, the coefficients *increased* compared to the values held in model two. The original levels held in model one were almost reached. This indicates that the true effect of credit rating codes is underestimated when the industry variables were left out. The difference between the average interest rates of all credit rating codes are statistically significant at the five per cent significance level except between AAA- and AA-rated companies in 2010, and between B- and C-rated companies in 2005. The difference in the average interest rate between B- and C-rated companies is significant and at least above one per cent for all other years except for in 2005. The large standard error of means relative to the value of the coefficient is caused by the limited number of observations. This leads to the insignificance of the interest rate in 2005. Had there been more C-rated companies in the sample, it is expected that the difference would be significant. This specific observation of insignificance is thus not considered a continuous tendency.

Applicable to all models, it is evident that the time period of the sample plays an important role in deciding the average interest rate. Looking at the illustration of the interest rate over time in figure 4.1 in the descriptive statistics, the peak in 2008 is very visible. Obviously, this peak was triggered by the financial crisis. After the crisis, the average interest rate did not return to its level prior to the crisis, but stabilized almost half a percentage point above. When dividing the interest rate into the categories of the credit rating codes, the same time pattern emerged for all codes. However, the large interest rate increase of C-rated companies from 2005 to 2006 was not expected. It might be a result of having too few observations of C-rated companies, as there were only 73 observations of these in 2006. However, there are few observations of C-rated companies *each* year. The reason for the pattern may have been brought on by a concern regarding the overheating of the market, thus “punishing” the most risky companies by demanding higher interest rate. However, the expectation is that all credit rating codes should be influenced in the same direction, like they do in the other years. 2006 was even the year with the lowest number of defaulted companies since 1998, see attachment 7.5. There is no clear explanation for the interest rate jump of C-rated companies from 2005 to 2006.

As mentioned earlier, a statistical significance level at five per cent indicates that there is a maximum five per cent chance of falsely rejecting the null hypothesis. However, statistical significance of the results alone is not adequate for assessing the “importance” of a variable. When a sample is large enough, statistical significance can be obtained even when the effect is miniscule. *Economic* (or substantive) significance reaches beyond statistics. This type of significance can be measured by asking “so what?” or “how much does it matter?” (Miller & Rodgers, 2008).

How likely is it that a company’s credit rating code changes? In other words, how likely is it that the differences detected in the analysis in fact influences a company? In table 5.1, the changes in the credit rating codes in the sample are documented as percentages. The row to the left is the initial code and the columns represent the credit rating codes after the change.

Table 5.1 Credit rating code changes within companies

	C (%)	*B (%)*	*A (%)*	*AA (%)*	*AAA (%)*	*Total (%)*
C	44.59	27.97	17.41	9.23	0.79	100.00
B	2.43	42.05	28.27	23.92	3.32	100.00
A	0.88	13.87	48.26	32.31	4.69	100.00
AA	0.27	4.73	18.89	57.70	18.42	100.00
AAA	0.15	1.36	6.52	42.58	49.39	100.00

Note: If the same company is down- or upgraded twice, these are reported as two observations.

The number of credit rating code changes is rather substantial. B-rated companies switch rating codes most frequently, with 57.95 per cent[27] down- or upgrades between 2005 and 2011. An upgrade is almost always more likely than a downgrade. The threshold for downgrading a company from any other rating code to a C-rating is large. This is natural when keeping Bisnode’s wording on C-ratings in mind. “...weak or bad economy with severe payment remarks”.

The frequent occurrence of a credit rating changes has been established. The statistical significance and economic consequences can be read from the tables presented in the section regarding results. An interest rate effect is most important when both the statistical and the economic significance are present *and* the change occurs frequently.

[27] 100 per cent - 42.05 per cent.

When moving *one* notch from the AA-rating, insignificant results are detected in both directions. Therefore, despite the frequent changes occurring from a company rated AA seen in table 5.1, these are not expected to lead to large interest rate changes. The interest rate difference between the A- and the AAA-rating is deemed insignificant twice in model two, but are significant again in model three, when including the industry categories. Changes between these two credit rating codes do not occur frequently. The changes from C- to B-rating are frequent as well as economically significant. Generally, they are also considered statistically significant, regardless of the single insignificant occurrence in 2005. The one-notch change between a B-rating and an A-rating occurs frequently and is also deemed both statistically and economically significant.

The remaining changes refer to statistically significant changes where multiple notches are taken in one swap, and the economic consequences are rather large. Surprisingly, there are many upgrades from a C-rating to an A-rating as well from a B-rating to an AA-rating.

It is not given that it is *easy* for a company to change a credit rating code in a favorable direction. It takes effort to improve company ratios and other parameters influencing the credit rating. However, with knowledge of and focus on these parameters, it may be achievable.

When a firm's size increases, the reductions in its interest rate is statistically significant for all three models. This result signalizes the same as Petersen and Rajan (1994) did in their study. The large size of the debtor reduces the perceived risk of borrowing money to him/her and a "discount" embodied as a lower interest rate is thus given by the creditor. However, the economic effect is minor. When size increases with NOK 100 000 (which is a possible outcome as the average size is NOK 2 410 000), the coefficients in the models show that the interest rate decreases approximately 0.02 to 0.04 per cent. This does not benefit the debtor much. The definition of size should also be evaluated. An increased size can be financed by both debt and/or equity. If a firm's increased asset stock is financed by debt, this would most likely not lead to a decreased interest rate, and also not to an increased securitization opportunity. This fact may have contributed to reduce the impact of a change in size on the interest rate. Also, if assets are debt financed they will hardly qualify as security.

The assumption regarding the year of incorporation was that well-established companies, having been in the business for longer periods, would be more able to acquire favorable deals with creditors. The year of incorporation is only significant in 2005 in all three models and the results express that older companies hold *higher* interest rates than younger companies. This is the opposite of what was expected by Eklund, Larsen, and Bernhardsen (2001) and Svendsen (2005). Generally, it is not expected that younger companies will receive more favorable interest rates than older companies. However, the economic consequence is scarce. According to the regression results in model three, aging a *100* years would lead to an increased interest rate of 0.800 per cent, if other variables were kept constant. Overall, this variable is not considered an influential variable due to the large amount of insignificant results.

Contributing even more to the weak results is the fact that, for some years of incorporation, the average interest rate is calculated based on a small number of observations. For example in 1870, there were three observations and the average interest rate was calculated as 1.526 per cent. In 1885 there were four observations and the average interest rate was 9.391 per cent. Having a small number of observations makes the results less trustworthy.

In model three, the liquidity ratio compared is significant in 2005, 2006, 2007, 2010 and 2011. On the one hand, this indicates that variables compared to industry averages indeed can be important factors, which Bisnode should consider adding to their model. On the other hand, the large standard errors compared to the value of the coefficients contribute to make the t-values low. This implies uncertainty around the value and thus only modest significance. Also, changing the liquidity ratio compared by one whole unit is difficult. If a company has a liquidity ratio of one and the industry has a ratio of two, the company has to *triple* its liquidity ratio in order to increase the liquidity ratio compared by one unit. And this only applies if the industry liquidity ratio keeps constant. Even when this is achieved, the positive gains are small. In model three the interest rate decreases, on average, 0.073 per cent if the liquidity ratio compared increases by one unit[28]. A reason contributing to the small effect may be the spread of the distribution of the variable. The variable is self-generated by the author of this thesis and comprises *two* fractions. Depending on the relative size of these fractions, the values can become very large, increasing the distribution of the spread and greatly influencing the results.

[28] Only the significant results are included in the calculation.

The interest rate differences among industries are large, therefore, the risk associated with different industries is assumed to vary considerably. Trade, construction, manufacturing and oil/gas/mining are the industries contributing with the highest average interest rates compared to real estate's interest rate. The performances of these industries are dependent on economic cycles. The time pattern discussed in conjunction with the credit rating codes may of course also influence the average interest rates affiliated to different industry categories. Trade and construction were especially hit by the financial crisis, holding average interest rates above ten per cent in 2008. According to Svendsen (2005), these two sectors have the greatest risk of default. In 2009, the average interest rate noticeably decreased for all industries except the oil/gas/mining industry. This coincides with the spot crude oil price decreasing approximately 37 per cent from 2008 to 2009, due to the reduced demand caused by the economic setback (OPEC, 2013). This industry would thus suffer from the crisis in a longer time period than other industries. Real estate is the industry with the lowest average interest rates, as a company within this industry has good opportunities to provide security for its loans, mentioned in section 2.1. The same applies to the energy industry, if it entails power plants, and the shipping industry, with its ship supply (however, the value of ships may vary considerably). The interest rate difference between an energy company and a real estate company is insignificant in three out of seven years. The companies affiliated with the energy industry are also the only companies that reach a lower level of average interest rate after the crisis as prior to the crisis. The difference between real estate's interest rate and shipping's interest rate is insignificant in three out of seven years (before the crisis). All other industries have statistically significant and larger average interest rates than the real estate business. Even though the differences in interest rates among industries are considered large, most most companies only rarely change industry affiliation within its existence (it has happened 300 times in this data set). Thus companies cannot actively use this knowledge to gain more favorable interest rates.

The partly unexplained increase in the interest rate of C-rated companies from 2005 to 2006 is not an apparent pattern within the industries.

The R^2_{adj} of model one is weak. During the financial crisis it slightly increases. Greater interest rate differences between AAA-rated and C-rated companies were detected and C-rated companies were especially "punished" for belonging to this category. The amount of defaults also started increasing (attachment 7.5) and the credit rating codes were able to capture some of this.

Even though the R^2_{adj} of model two and three are larger than that of model one, the level of explanatory power is still low. The relatively larger increase in the R^2_{adj} in 2008 presented in model two compared to model one (the steeper slope in figure 4.12) may be caused by market players acting safer, and thus starting to undergo more thorough risk evaluations *beyond* credit ratings. With the unstable market situation in mind, a creditor may deem it necessary to evaluate a greater *sphere* around a potential debtor in order to cover the risks appropriately.

5.2 Implications

As the interest rate is generated on an aggregated level, the conclusion only applies to that level. It would be preferable to be able to link interest rates to their original sources and to analyze *each* credit category's interest rate level in light of a company's assigned credit rating code. At least gaining more knowledge on the "unspecified long-term financial debt" would increase this opportunity. Perhaps some credits are given at more favorable rates than others, and underlying reasons could be sought out. However, obtaining more details regarding the dependent variable could easily have made the study too large, considering the scope and time limits.

As mentioned in section 3.8 regarding validity, the size of the companies' interest rates have not been weighed with the size of their interest-bearing debt, allowing each company's interest rate to matter equally. It is expected that the preciseness of the results would increase if the interest rates in the data set could be weighed. This would not allow small loans to impact the results equally to large loans, as is the case in this paper.

Four control variables were selected. Using even more could increase accuracy. The rating codes consist of aggregated information and many potential control variables deriving from the accounts were already a part of these codes. However, information regarding securities would, for example, be of interest. This variable was included in the data set, but with too few observations. As the goal of this thesis was to analyze the relationship between the average interest rate and the credit rating codes, the information in the data set was, nevertheless, sufficient.

Despite not being discussed in details, not all credit is extended based on rational credit evaluations. At times, the competitive ambience may steer the price of credit. A strong economy leading to intensified competition towards credit customers may result in interest rates being competed downwards, even lower than a credit evaluation would predict. This effect could perhaps be captured by applying more macroeconomic parameters, influencing the demand and supply of credit. These parameters change over *time* and the data must thus be handled as panel data. A simplified solution could be to extract the effect of time by adding dummy variables representing each year.

Further research can be based on resolving the implications mentioned above. Other issues extending this thesis could be expanding the sample by adding additional years. A large sample contributes to make conclusions more reliable. The initial data set had over 3 million observations. One of the limitations of SNF's data set was that the credit rating codes were only available in seven out of 20 years. This reduced the sample greatly. There were also very few C-rated companies, making these observations less trustworthy.

Experian's credit rating codes could be included and compared to Bisnode's rating codes, endeavoring to detect potential rating code differences and to search for underlying reasons. For credit issued by institutions with *internal* credit rating procedures, it would also be of interest to match *their* codes with Bisnode's codes. To what extent do Bisnode's codes differ from the credit extender's internal credit rating codes?

If focus is kept on Bisnode, its rating foundation could be split up in its four main pillars mentioned in section 3.5.2, observing at what extent each aspect influences the interest rate relative to each other.

5.3 Conclusion

Based on current knowledge, the main research question has been answered. Increased creditworthiness leads to a decreased average interest rate, and the relationship is statistically significant. In other words, the worthiness level attributed to a firm through credit rating codes clearly contributes to dictate the level of the interest rate of a company. However, one should be careful applying this conclusion to the interest rate deviations between AA- and AAA-rated companies as well as between AA- and A-rated companies. The reason is a detection of insignificant results, which are also expected to continue in the future.

These findings lead to the assumption that creditors accept a certain amount of credit risk as long as it is reflected in the interest rate. This result is comprehensible as risk aversion is assumed to be fundamental in the average Norwegian mind-set.

The credit rating codes of Bisnode are not part of any nation-wide regulations, like the rating codes of the big three CRAs are. Nevertheless, the frequent rating code changes detected together with the evident economic consequences underline the impact of Bisnode’s codes on the average interest rates of Norwegian companies. These companies should thus be aware of the key indicators applied by Bisnode in its AAA-rating system.

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7. Appendix

7.1 Registered and certified CRAs in the European Union

Name of CRAs
Euler Hermes Rating GmbH
Japan Credit Rating Agency Ltd
Feri EuroRating Services AG
BCRA-Credit Rating Agency AD
Creditreform Rating AG
Scope Ratings GmbH
ICAP Group SA
GBB-Rating Gesellschaft für Bonitätsbeurteilung GmbH
Assekurata, Assekuranz rating-Agentur GmbH
ARC Ratings, S.A. (previously Companhia Portuguesa de Rating, S.A)
AM Best Europe-Rating Services Ltd. (AMBERS)
DBRS Ratings Limited
Fitch France S.A.S.
Fitch Deutschland GmbH
Fitch Italia S.p.A.
Fitch Polska S.A.
Fitch Ratings España S.A.U.
Fitch Ratings Limited
Fitch Ratings CIS Limited
Moody’s Investors Service Cyprus Ltd
Moody’s France S.A.S.
Moody’s Deutschland GmbH
Moody’s Italia S.r.l.
Moody’s Investors Service España S.A.
Moody’s Investors Service Ltd
Standard & Poor’s Credit Market Services France S.A.S.
Standard & Poor’s Credit Market Services Italy S.r.l.
Standard & Poor’s Credit Market Services Europe Limited
CRIF S.p.A.
Capital Intelligence (Cyprus) Ltd
European Rating Agency, a.s.
Axesor SA
Cerved Rating Agency S.p.A. (previoulsy CERVED Group S.p.A.)
Kroll Bond Rating Agency
The Economist Intelligence Unit Ltd
Dagong Europe Credit Rating Srl (Dagong Europe)
Spread Research
EuroRating Sp. z o.o.

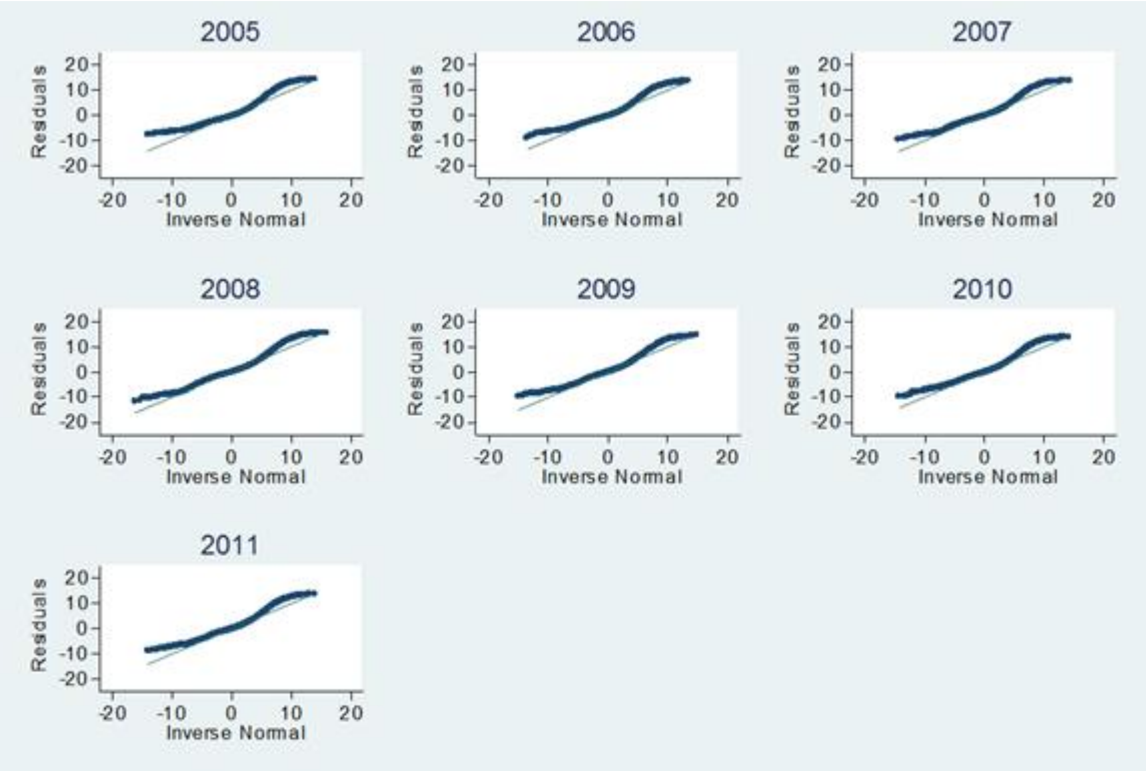
Source: (ESMA, 2014)

7.2 Registered NRSROs in the United States

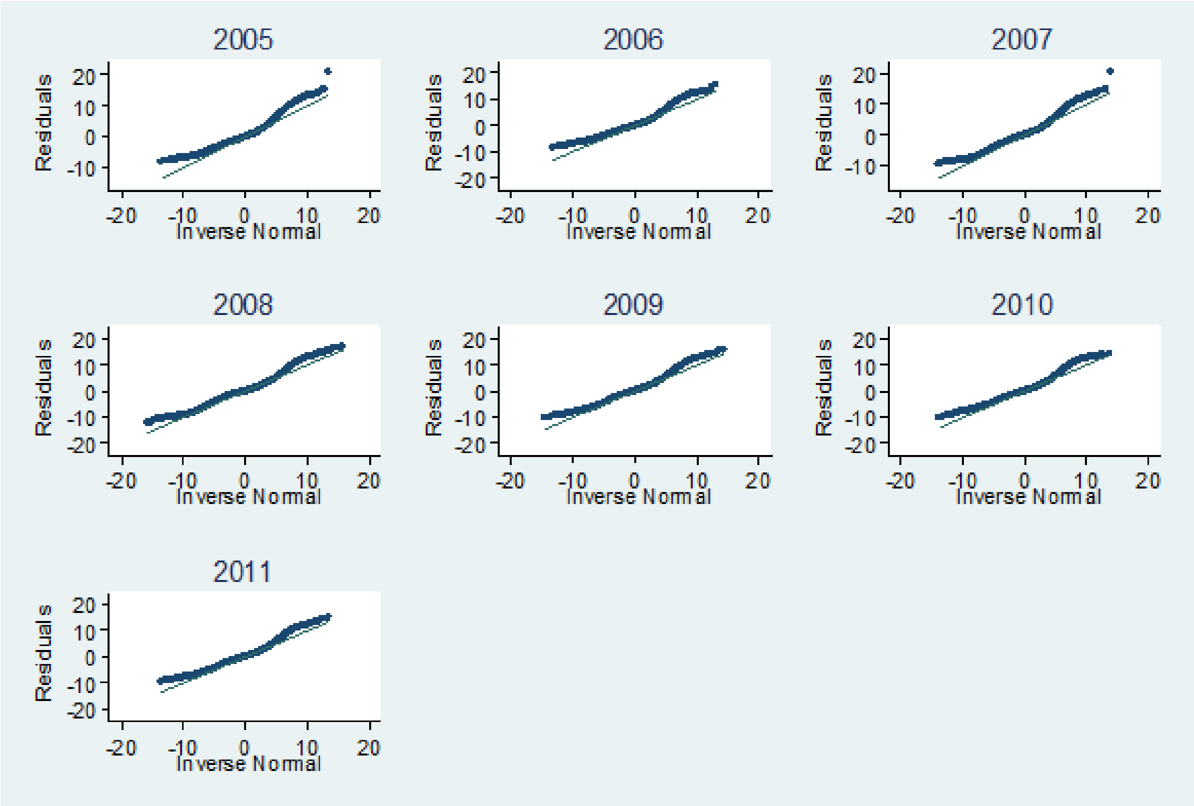
Name of CRAs
A.M. Best Company, Inc.
DBRS, Inc.
Egan-Jones Ratings Co.
Fitch, Inc.
HR Ratings de México, S.A. de C.V.
Japan Credit Rating Agency, Ltd.
Kroll Bond Rating Agency, Inc.
Moody's Investors Service, Inc.
Morningstar Credit Ratings, LLC
Standard & Poor's Ratings Services

Source: (SEC, 2014 a)

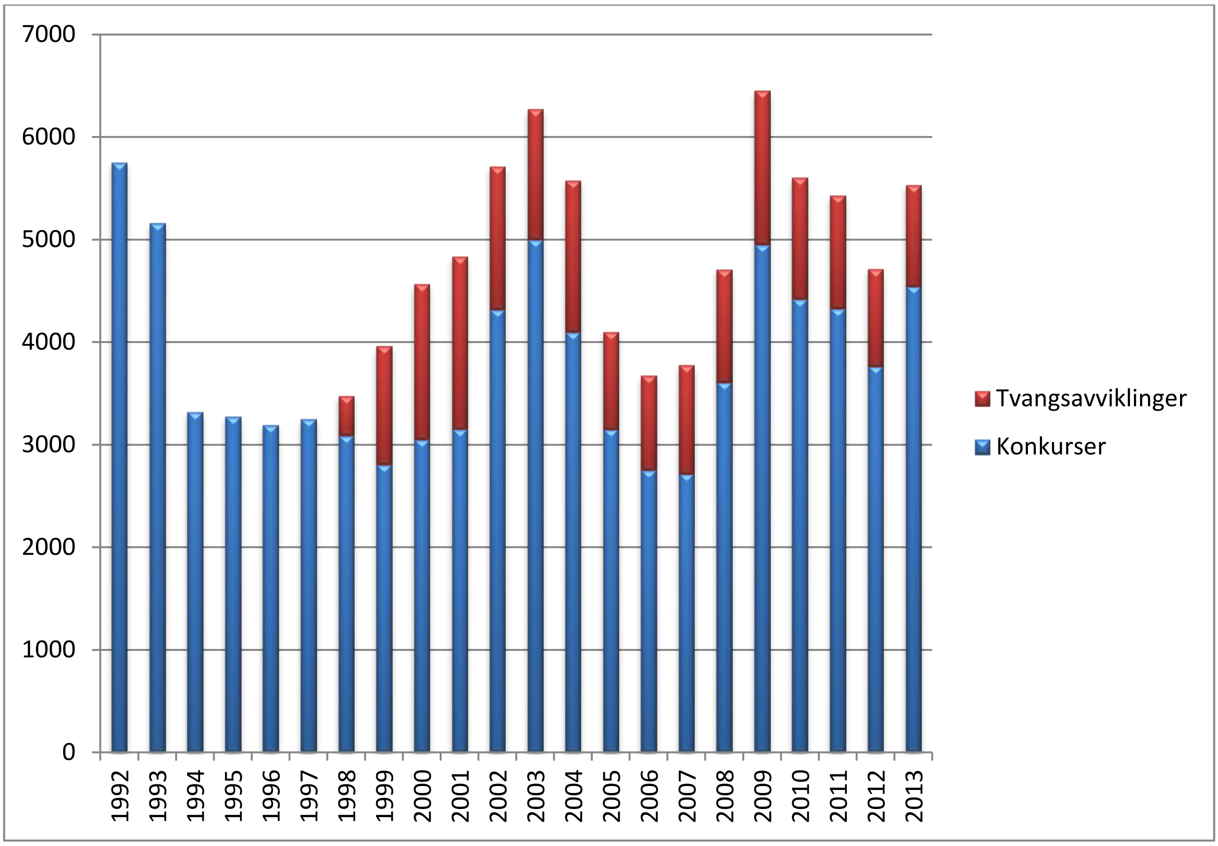
7.3 The distribution of the residuals in q-q plots, model one



7.4 The distribution of the residuals in q-q plots, model three



7.5 The development of defaults from 1992 to 2013



Note: Tvangsavviklinger= Forced liquidations, Konkurser= Defaults
When printed in black and white, the top part of the histograms starting from 1998 is the forced liquidations.
Source: Per Einar Ruud, with permission to copy

7.6 Stata commands for processing the data

```
*Generating the interest rate variable
bysort orgnr (aar): gen interest_rate=(2*rentekost)/(rgjeld_min + rgjeld_min[_n-1]) ///
if rgjeld_min[_n-1]!=. & rgjeld_min!=. & rgjeld_min>0 & rgjeld_min[_n-1]>0
gen interest_rate100=interest_rate*100

*Generating the rating codes as dummy variables
tab ratingkode, generate(ratingD)

*Generating the industries as dummy variables
tab bransje, generate(bransjeD)

*Generating the size variable
bysort orgnr (aar): gen snitt_sumeiend=((sumeiend + sumeiend[_n-1])/2)
gen snitt_sumeiend100=snitt_sumeiend/100

*Generating the liquidity ratio compared variable
gen snitt_oml=((oml+oml[_n-1])/2)
gen snitt_kgjeld=((kgjeld+kgjeld[_n-1])/2)
bysort orgnr (aar): gen snitt_lr=snitt_oml/snitt_kgjeld
bysort bransje: egen snitt_lrbransje=mean(snitt_lr)
```

```
gen snitt_lr_på_bransje=snitt_lr/snitt_lrbransje


*Processing the data
keep if ratingkode>0
keep if ratingkode<9
keep if aktiv==1
drop if konkaar!=0

drop if mors_orgnr!=.        //group posts in the income statement:
drop if invdtrres!=0
drop if invtsres!=0
drop if rentintkons!=0
drop if rentekostkon!=0
drop if minintr!=0
drop if konsbid!=0
drop if invdtr!=0            //group posts in the balance sheet
drop if invkonsbal!=0
drop if laankonl!=0
drop if laankonk!=0
drop if laanan!=0
drop if andrinv!=0
drop if aksjkons!=0
drop if konsgl!=0
drop if konsgk!=0
drop if skyldkid!=0
drop if minintbal!=0

keep if salgsinn>0
drop if oml<0
drop if anl<0
keep if ek>0
drop if kgjeld<0
drop if lgjeld<0

keep if interest_rate>0

keep if selskat==1           // limited liability only
drop if bransje==10          // no finance
drop if bransje==13          // no R&D
drop if eierstruktur==5      // no public

*removing missing data
keep if bransje!=.
keep if stiftaar!=.
keep if interest_rate!=.

*testing for missing data
misstable summarize

*Replacing obvious input errors
replace stiftaar = 2000 if stiftaar==2
replace stiftaar = 1990 if stiftaar==1.99
replace stiftaar = 2001 if stiftaar==2.01

*Keeping relevant years
keep if aar>2004

***
*Trimming the data set
*Applying the 95 percentile to certain posts
*PS, this is executed for each year separately
***
egen p95_oml=pctile(oml), p(95)
```

```
drop if oml>p95_oml

egen p95_anl=pctile(anl), p(95)
drop if anl>p95_anl

egen p95_ek=pctile(ek), p(95)
drop if ek>p95_ek

egen p95_kgjeld=pctile(kgjeld), p(95)
drop if kgjeld>p95_kgjeld

egen p95_lgjeld=pctile(lgjeld), p(95)
drop if lgjeld>p95_lgjeld

egen p95_salgsinn=pctile(salgsinn), p(95)
drop if salgsinn>p95_salgsinn

egen p95=pctile(interest_rate), p(95)
drop if interest_rate>p95

*regression model one
bysort aar: reg interest_rate100 ratingD1 ratingD2 ratingD3 ratingD4, ///
robust cluster(orgnr)

*regression model two
bysort aar: reg interest_rate100 ratingD1 ratingD2 ratingD3 ratingD4 ///
snitt_sumeiend100 stiftaar snitt_lr_på_bransje, robust cluster(orgnr)

*regression model three
bysort aar: reg interest_rate100 ratingD1 ratingD2 ratingD3 ratingD4 ///
snitt_sumeiend100 stiftaar snitt_lr_på_bransje bransjeD1 bransjeD2 ///
bransjeD3 bransjeD4 bransjeD5 bransjeD6 bransjeD7 bransjeD8 ///
bransjeD9 bransjeD11 bransjeD12, robust cluster(orgnr)
```