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Credit Rating Methodology

Lifting the lid to the black box:
Assessing the need of industry-specific models that can replicate credit ratings assigned by Moody's

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Abstract

The methodology of credit rating agencies is somewhat secretive and can to a large extent be likened to a black box. The rating agencies claim that any attempt to replicate their ratings is doomed to fail. Previous research suggests the opposite by proving that a large part of a rating can be replicated by financial data. These studies have lifted the lid to the black box and created a better understanding of what underlies any given rating. However, no study has assessed whether, how, and why a replicating model differs depending on the industry the data sample is based upon.

This thesis takes a first step in this direction. By means of multivariate logistic regression, two industry-specific models are created: one that is based on a sample of 147 issuers in the oil & gas industry and another that is based on 78 issuers in the consumer products industry. A third model that incorporates the whole data sample is thereafter created to assess the predictive power of the industry-specific models. The industrial differences are analyzed in light of Porter's Five Forces.

Results reveal that certain industrial differences must be accounted for, while fundamental factors that impact the ability to meet debt payments are similar across both industries. Accounting for all rating categories, the consumer products model is able to predict 53% of the rated firms (oil & gas 41%). Accounting for two rating categories, investment grade and speculative grade, the consumer products model is able to predict 85% of the rated firms (oil & gas 74%). The concordance rates in both models are far from acceptable for any practical usage of the models. However, the ability to predict credit ratings is higher in the industry-specific models than in the model that incorporates the whole data sample. Moreover, the variables in the final rating models are statistically significant, and they differ between the models. For that reason it is concluded that there is a need for industry-specific credit rating models.

Key words: Credit Rating Methodology, Moody's, Multivariate Logistic Regression, Porter's Five Force

Abstract

De metoder som kreditvurderingsbureauerne benytter sig af er omgærdet med stor hemmelighed og kan i stort omfang sammenlignes med en flyvemaskines sort boks. Kreditvurderingsbureauerne hævder at det er umuligt at efterligne deres vurderinger. Alligevel viser forskning på området at størstedelen af en vurdering kan blive (genberegnet) på baggrund af finansielle data. Denne forskning har åbnet den sorte boks og bidraget til en bedre forståelse af hvilke faktorer der ligger til grund for en vilkårlig vurdering. Ingen forskning har dog undersøgt hvordan og hvorfor en rekonstrueret beregningsmodel er anderledes alt afhængigt af hvilken industri datagrundlaget er baseret på.

Denne afhandling tager et første skridt i denne retning. To industri-specifikke modeller er konstrueret ved at anvende multivariat logistisk regression. Den første model er konstrueret på baggrund af data fra 147 virksomheder inden for olie- og gas industrien. Den anden model er konstrueret på baggrund af data fra 78 virksomheder inden for forbrugsgoder industrien. En tredje model er derefter konstrueret på baggrund af det samlede datagrundlag for at vurdere præcisionen af de to industri-specifikke modeller. De industrielle forskelle er analyseret i et Porter's Five Forces perspektiv.

Resultaterne viser at der må tages hensyn til bestemte industri-specifikke forskelle mens at fundamentale industri-specifikke faktorer der påvirker virksomhedernes evne til at tilbagebetale gæld er ens begge industrier imellem. Modellen for forbrugergoder forudsiger 53 % af virksomhedernes vurderinger når alle vurderingskategorier tages i betragtning (41 % inden for olie og gas). Modellen for forbrugsgoder forudsiger 85 % af virksomhedernes vurderinger når to vurderingskategorier tages i betragtning (74 % inden for olie og gas). Præcisionen for begge modeller er langt fra tilfredsstillende i forhold til at modellerne kan bruges i nogen form for praksis. De industri-specifikke modeller har dog en større evne til at forudsige kredit vurderinger sammenlignet med model 3 der benytter det samlede datagrundlag. Derudover er variablerne i de endelige vurderingsmodeller statistisk signifikante og de varierer modellerne i mellem. På denne baggrund konkluderes det at der er et behov for industri-specifikke kredit vurderings modeller.

1. Introduction

> There are two super powers in the world today in my opinion. There is United States and there is Moody's. United States can destroy you by dropping bombs, and Moody's can destroy you by downgrading your bonds. And believe me, it is not clear sometimes who is more powerful (Friedman 2011, p.1)

1.1. Background

The modern financial system stood on the brink of its demise during a few months in late 2008. The decision taken by the major credit rating agencies (CRAs) to downgrade nearly $14 trillion of investment grade bonds to junk status shocked the global financial markets and accelerated an economic decline yet unprecedented in present time (Scalet & Kelly 2012). Although the failures underlying the Global Financial Crisis (GFC) of 2008-2009 relate to the building blocks of the entire financial system, few had to carry the can for the crisis as extensively as the rating agencies did. Accused of being 'uncontrolled world powers' and 'pyromaniac weathermen', they had by the time of the crisis grown into exerting a tremendous impact on global economic stability (Caouette, Altman & Narayanan 2008, p.81; Langohr & Langohr 2011, p.15). However, while the credit rating agencies were subjected to the most extensive public criticism during the crisis, their ability to accurately assess creditworthiness had been questioned for a long time by market participants.

During the last two decades, credit rating agencies have failed to blow the whistle ahead of several credit crises. Besides belatedly identifying sovereign default disasters in Southeast Asia in 1997, the United States in 2001-2002, and Europe in 2002-2003, the CRAs missed to spot firm-specific defaults such as the Enron, WorldCom, and Parmalat collapses in the period 2002-2003 (Langohr & Langohr 2011). In the latter case, all three firms were considered to be highly creditworthy shortly before they had to declare bankruptcy. Although the rating agencies to some extent managed to weather these storms, the magnitude of the GFC ascertained the previous concerns and pointed to a new reality – something was deeply amiss with the rating industry and market participants could no longer rely on credit ratings. Perhaps, it was rather a wake-up call into a more correct reality.

Because what is really a credit rating, for what reasons have the credit rating agencies been criticized, and what role do they fulfill in the financial system? Reviewing each of these questions might unfold the actual and existing problem with credit ratings.

1.2. Problem identification

Credit ratings are often misunderstood. As the examples above indicate, CRAs do not possess a crystal ball. They cannot see if and when a specific default will occur. This is because ratings are descriptive, rather than prescriptive, of a debt situation. CRAs do not provide recommendations about buying, selling, or holding a particular security. Their ratings express nothing more than independent opinions about creditworthiness (Caouette, Altman & Narayanan 2008).

The *raison d´être* of rating agencies is to resolve information asymmetry between investors and issuers by objectively measuring credit risk (Langohr & Langohr 2011). By doing so, CRAs serve the interests of the entire financial system by reducing the transaction costs for all market participants. The unique role in overcoming information asymmetry is the context in which rating agencies operate within and where they add economic value (Langohr & Langohr 2011).

However, several aspects related to the structure and procedures of the rating agencies have either led to the misuse of ratings or prevented them from fulfilling their true function. Criticism has mainly revolved around three issues: the regulatory dependence on ratings, the issuer-pay model, and the lack of transparency in the rating methodology (Scalet & Kelly 2012).

In terms of regulatory dependence, two decisions were taken by the Securities and Exchange Commission (the SEC) in 1973 that changed the rating industry fundamentally; the first securities rule that formally incorporated credit ratings was promulgated, and a limited class of "Nationally Recognized Statistical Rating Organizations" (NRSRO) was designated. While the barriers to enter the rating industry skyrocketed, the CRAs were granted regulatory licenses that gradually elevated their importance for decades. Protected under the first amendment, the agencies were practically immune from lawsuits regardless of the accuracy of their ratings (Scalet & Kelly 2012). More than three decades later, this regulatory dependence would shake the foundations of the global economy.

By December 2008, the market for structured financial products accounted for 35% of the total outstanding bond market in the US. More than half were given a triple-A rating by Moody's (Benmelech & Dlugosz 2012). Disregarding the complexity of these products, and perhaps blinded by irrational exuberance, the contemporary regulatory framework allowed investors to consider ratings as authorized seals of approval and use them as a substitute for their own analysis.

Following the GFC, policymakers in the U.S. diminished the regulatory use of ratings. The implementation of the 2010 Dodd-Frank Wall Street Reform Act reduced the role of CRAs in making investment decisions, nullified their legal protection, and eliminated the NRSRO designation (Scalet & Kelly 2012). Although the market for credit ratings still is highly concentrated, the SEC has evidently proposed changes to encourage more competition.

The second criticism concerns the issuer-pay compensation model. In contrast to the problems with regulatory dependence, questions regarding the compensation model remain unanswered. On one hand, the issuer-pay model introduces a potential conflict of interest whereby an agency may act in the interest of its client rather than producing an accurate rating. On the other hand, fewer bonds would be rated in a subscriber-pay model because only a limited number of investors would afford to pay for the information. Such a scenario would increase information asymmetry and market inefficiency and thereby counteract the aforementioned true purpose of ratings. The issuer-pay model is not flawless, but it reduces asymmetric information and market inefficiency since the ratings are publicly available (Scalet & Kelly 2012).

The last criticism concerns the lack of transparency in the rating methodology. In response to the GFC, the Bank for International Settlements (2008) initiated an investigation to examine the problems and address the weaknesses surrounding the credit rating industry. The primary purpose was to determine how to avoid a similar turmoil in the future. By highlighting the importance of increased transparency, the key conclusion was that the CRAs must clarify the motives behind their ratings to a larger extent. However, the recommendation can to a large extent be seen as an intrusion on the rating agencies' profession area. To remain prominent, rating agencies cannot reveal the details of how their ratings are determined.

Perhaps, as Scarlet & Kelly pinpoint in their study on the ethics of CRAs, this is exactly what needs to be done (Scalet & Kelly 2012, p. 483):

> The industry has always faced the tension between concealing a proprietary rating process within a competitive market and investors' desire for increased public disclosure about the rating process. The most recent failures have led to an outcry for more information about the process that created the rating. What is the methodology?

Credit rating agencies will remain omnipresent in the global financial system. Even though their performance has not been without blemish, the global financial markets still need their essential informational services. Their assessment of the creditworthiness of sovereigns, corporations and various financial instruments will continue to influence the behavior of almost all participants on the capital market. Regulators will use their expertise to monitor the solvency of banks and other financial institutions, institutional investors will take into account ratings in their policies for fixed-income investments, and the borrowing cost of issuers will continue to depend on the rating obtained.

While measures have been taken to address the issues with regulatory dependence, and while the debate concerning the compensation model remains unresolved, the problem with transparency remains. While market participants urge for greater transparency, the methodology of the major credit rating agencies remains somewhat secretive.

Herein lies the inspiration for this thesis.

1.3. Problem discussion

Financial data is just one of many aspects that rating agencies evaluate when they assess the creditworthiness of a bond issuer. Qualitative aspects ranging from business risk and market position to management skills and corporate governance are all accounted for when setting a rating. The analysis is also complemented with an evaluation of the prospects of a firm, which requires access to confidential data and informal confrontation with top executives. The rating process can to a large extent be likened to a black box – what happens at the rating meeting stays at the meeting. Therefore, CRAs claim that any attempt to replicate their ratings is doomed to fail (Kim, 2005).

Previous research suggests the opposite. Gray, Mirkovic & Ragunathan (2006) argue that even though CRAs incorporate qualitative analysis, a large part of the credit ratings can be explained by financial data. The statement is far from groundbreaking. For decades, financial ratios have been widely used by academics to evaluate credit risk. Already in 1968, Altman pioneered the use of financial ratios to predict corporate bankruptcy by developing what has become known as the Z-score model. By means of different statistical methods, several researchers including Pinches & Mingo (1973) and Kaplan & Urwitz (1979) successfully developed models that did not predict corporate default *per se*, but rather the credit ratings assigned by a rating agency. Like Altman, they did so by identifying the most significant financial variables.

A more recent study on replicating rating models was carried out by Resti (2002). While building the model on a European data sample, Resti (2002) discovered that the impact of operating revenues on rating forecasts differed between service and manufacturing firms. Although the discovery implied that industry sectors influence the prediction of a rating, the number of rated firms in Europe was too small for Resti to thoroughly examine the industrial differences.

Put together, these studies have lifted the lid to the black box and created a better understanding of what underlies any given rating. Put together, however, the proposed models have created a research gap that, to the author's knowledge, has not been investigated yet. The studies have been conducted in various geographical segments, they have been conducted using a variety of statistical methods, they have been based on ratings assigned by various credit rating agencies - but no study has clarified whether, how, and why a replicating model differs depending on the industry it is based upon. Is there a need for industry-specific replicating credit rating models to begin with?

The interpretation of quantitative variables will naturally change depending on the industry. The same financial ratio can have a different meaning for firms operating in different industries. For that reason, the performance of a rating model may be enhanced if it is trained and tested within the confines of a particular industry. An industry-specific model can as such illuminate the black box and contribute to the theoretical knowledge if it reveals that some financial variables are more significant than others in predicting credit ratings that are assigned to firms in different industries.

This paper takes a first step in this direction by creating one model that is based on a sample of issuers operating in the oil & gas industry and a second model that is based on issuers in the consumer products industry. Both industries exhibit distinguishing features that influence the interpretation of financial fundamentals, and presumably the explanatory power of certain ratios. A third model that incorporates the whole data sample is thereafter created to assess the predictive power of the industry-specific models. By structuring the analysis around four research questions, the main purpose is to examine whether there is a need for industry-specific credit rating models.

Besides bridging the research gap, an industry-specific model can also prove useful to unrated firms and investors alike. Unrated firms can use the model to determine their own unofficial and preliminary credit rating, while investors can use the model as a "rough-and-dirty" screening device when evaluating the creditworthiness of unrated firms that intend to enter the bond market.

1.4. Research questions

Is there a need for industry-specific replicating credit rating models?

1. To what extent can the industry-specific credit rating models predict the ratings assigned by Moody's?
2. Does the predictive power increase when a replicating credit rating model is developed inside the confines of a specific industry?
3. Which financial variables prove to be most significant in the replicating credit rating models, and do the variables differ between the three models?
4. Are the financial variables that have proved to be significant in earlier studies also significant in the industry-specific models?

1.5. Delimitations

1. The industry-specific models will attempt to replicate the ratings assigned by Moody's. Ratings assigned by other rating agencies will not be considered.
2. Moody's provides two types of ratings: issue-specific ratings and issuer specific-ratings. The former are assigned to particular debt issues, while the latter provides an opinion on the fundamental creditworthiness of an issuer. Issue-specific features do not bias issuer ratings. To make the empirical findings more reliable, it is deemed necessary to develop the replicating rating models based on issuer ratings.
3. Only issuers from the United States are included to circumvent the potential problem of country risk.
4. Moody's provide ratings with two time horizons: long-term ratings and short-term ratings. Short-term ratings are primarily concerned with the coming year and use a smaller rating scale than long-term ratings. For that reason, short-term ratings are excluded from the thesis.

Hence, the industry-specific models will attempt to replicate long-term ratings assigned by Moody's to US issuers.

1.6. Research design

The following paragraph is a brief description of the research design with the intention of providing a holistic view of the study. Chapter 6 describes the development of the models and discusses the validity and reliability of the research design in more detail.

The credit ratings are obtained from Moody's. The reason is that the ratings are easily available from the rating agency's official website. Previous research and relevant theories on the subject of credit risk is covered to identify the financial variables that are most likely to affect a credit rating. Previous research is also used to discover the most suitable statistical technique for developing the replicating credit rating models. The financial ratios are collected from the Bloomberg Professional Services Terminal. Once the data is collected, statistical and econometric techniques are applied to obtain the results, construct the models, appraise the research questions and draw the conclusions.

1.7. Disposition

Chapter 1 has been an introduction to the study, including the identification and discussion of the problem, the research questions, the necessary delimitations, and the research design.

Chapter 2 describes the advantages of issuing bonds when raising capital, and the purpose of credit ratings in so doing. Moody's rating scale, rating methodology, and rating process is also described.

Chapter 3 reviews some of the more significant papers on the topic of replicating rating models or bankruptcy prediction models in order to identify the most important financial ratios and the most suitable statistical technique.

Chapter 4 frames the findings from the previous chapter by explaining how the most important categories of financial ratios relate to credit risk.

Chapter 5 points out the similarities and differences between the oil & gas and the consumer products industry by analyzing them in light of Porter's Five Forces.

Chapter 6 describes the model development process, presents the financial variables that are tested and discusses the reliability and validity of the study.

Chapter 7 presents and analyzes the results of each step of the model development process.

Chapter 8 concludes the study by answering the research questions and providing suggestions for future research.

A detailed introduction that explains the purpose and outline of a chapter is given when necessary.

2. Credit Ratings

Chapter 2 begins by reviewing the means by which a firm can raise capital in light of the pecking-order theory. The advantages of issuing bonds are highlighted, and the basics of bonds are described. Akerlof's 'Lemons Problem' is applied on the credit market to emphasize the importance of credit ratings in decreasing asymmetric information. Attention is then given to Moody's rating scale, rating methodology, and rating process. By putting these pieces of the puzzle together, the intention of this chapter is to provide a thorough understanding of the need of credit ratings and the obstacles faced when trying to replicate them.

2.1. The pecking-order theory

In order to finance long-term investments, cover operational expenses, or carry out major projects, companies must raise capital. This can be done in several ways. Firstly, a company might enjoy organic growth by re-investing profits from current operations. However, organic growth rarely generates adequate financial means, especially not for companies that are looking to expand through growth or acquisition. Secondly, a company can raise equity capital by selling shares of ownership. The decision to bring in new owners is rather unpopular among existing shareholders because it dilutes their ownership. It is also the most expensive route to capital. Thirdly, a company can borrow money from a bank. A bank loan is rather inflexible and the interest rate might be relatively high. It is relatively high, because there is a cheaper way for companies to borrow money– by issuing bonds (Choudhry, 2004).

The choice between internal and external finance is influenced by asymmetric information because managers know more about the risks and prospects of their firms' than outside investors. This introduces a pecking order of financing choices, whereby firms primarily prefer to finance investments internally, thereafter through issuing debt, and as a last resort by raising equity (ed. Brealey, Myers & Allen 2010). The theory suggests that the reason why profitable firms in general are less indebted is not because of low target debt ratios, but because they do not have to rely on external financing. The pecking order theory emphasizes the importance of financial slack. By having access to liquid assets such as cash, marketable securities, or spare debt capacity, a firm can finance profitable investments as they appear.

However, without any growth opportunities, financial slack can tempt managers to expand their perks or engage in empire building. Debt can be seen as a remedy to such extravagant behaviour. Periodical interest and principal payments are contractual obligations; they force bond issuers to pay out cash, they disciplines managers, and they incentivize improvements in operating efficiency.

Bonds provide further advantages in comparison to the other external means of raising capital. In comparison to a bank loan, bonds reduce the dependence on a certain creditor and unlock a wide range of financing alternatives in terms of currencies, sizes, geographies, and maturities of instruments (Langohr & Langohr, 2011). In comparison to dividends on equity, interest payments to bondholders are tax deductible for bond issuers. Since bond issues often are very large, they are split into smaller fractions in order to make them more marketable. The tradability of bonds is another favorable feature that increases the propensity among investors to lend a company funds.

There is a large diversity of bond instruments. Among others, there are non-conventional bonds such as floating rate notes, index-linked bonds, zero-coupon bonds, securitized bonds, and bonds with embedded options. The most basic type of bonds, sometimes referred to as a "plain vanilla bond", is a loan from one entity to another in return for periodic interest payments up until the day the loan is terminated. Despite the variety of bonds, the plain vanilla bond is still the most frequently issued debt instrument (Choudhry, 2004). To understand the purpose of credit ratings, and ultimately the purpose of trying to replicate them, the features of these conventional bonds are described in the following section. The other types of bonds are disregarded as they are outside the scope of this thesis.

2.2. Bond basics

A conventional bond is a fixed-income security that pays a periodical interest rate over a fixed time period. The periodical interest rate is called the coupon rate and the annual amount of the interest payments is the coupon. The number of years during which the coupon is paid by the issuer to the bondholder is referred to as the term to maturity. At the maturity date, the issuer redeems the bond by paying a final interest payment and a principal value of the loan proceeds. After that, the bond ceases to exist (Choudhry, 2004). Equation 2.2 on the next page demonstrates the pricing structure of a basic coupon bond with n years to maturity.

Equation 2.2 – *Present value of an n-year coupon bond*

$$P_0 = \frac{C}{(1+i)} + \frac{C}{(1+i)^2} + \cdots + \frac{C}{(1+i)^n} + \frac{M}{(1+i)^n}$$

C = coupon
n = number of payments
i = interest rate (required yield)
M = value at maturity (par value)

The price of a bond is the sum of the present values of all the expected coupons and the present value of the principal at maturity. A bond is as such a collection of cash flows, and these are discounted by an interest rate that is required by the bondholders. The required yield is based on the yield offered by comparable bonds on the market with a similar maturity and credit quality. Bond yields are quoted as credit spreads – i.e. the difference between the bond yield and an equivalent government bond.

Since the price of a bond is calculated as the present value of the future cash flows, a change in the credit spread will affect the bond price. When the required yield increases, the present value of the cash flows decreases and the bond becomes relatively unattractive to hold. When the market interest rate decreases, investors find it less attractive to hold a new bond and hence the price of the existent bond increases.

Credit spreads fluctuate for a number of reasons, and the relationship between spreads and credit risk is called the 'credit puzzle' due to its complexity[1]. This paper abstracts from this issue, but provides Table 2.2 to illustrate that a principal reason of credit spreads is how the market perceives a borrower: the spread is higher for lower rated bonds across all maturities. The nature of the issuer is a distinguishing feature of a bond, and the perception is reflected in the rating. Recalling that insiders are better informed than outsiders, this introduces the concept of asymmetric information.

Table 2.2 – *Average credit spreads in the industrial sector 1987-1996 (Elton et al 2001, p.253)*

	2	3	4	5	6	7	8	9	10
Aa	0.414	0.419	0.455	0.493	0.526	0.552	0.573	0.589	0.603
A	0.621	0.680	0.715	0.738	0.753	0.764	0.773	0.779	0.785
BBB	1.167	1.205	1.210	1.205	1.199	1.193	1.188	1.184	1.180

[1] For more information about the 'credit puzzle', see Elton et al, 2001, 'Explaining the Rate Spread on Corporate Bonds', *The Journal of Finance,* Vol.56, No. 1, pp. 247-277

2.3. Credit ratings as a solution to Akerlof's 'Lemons Problem'

The concept of asymmetric information, wherein rating agencies operate and add economic value, is deep-rooted in economic theory. Perhaps the most recognized paper in the world of finance regarding asymmetric information is the work of George Akerlof (1970), for which he received the 2001 Nobel Prize in Economics (Hendrikse 2003).

Akerlof illustrated the concept of asymmetric information by exemplifying a market for two types of used cars, high-quality cars (creampuffs) and low-quality cars (lemons). In Akerlof's hypothetical example, information asymmetry arises because the seller knows the quality of his car, while the buyer does not. Since buyers are unable to distinguish between creampuffs and lemons, they will offer the same reduced price for all cars. High-quality cars will not be offered for sale because the sellers of the creampuffs are unable to signal their higher quality and are unwilling to sell at a discount. Consequently, because of asymmetric information, the market will only contain lemons. Asymmetric information constitute the cornerstone of the credit rating industry, and the lemons principle can by all means be applied on the credit market in order to illustrate the importance of credit ratings.

Because of asymmetric information, potential bondholders are not able to distinguish high-risk issuers from low-risk issuers. An interest rate that covers the risk of lending funds to a high-risk borrower will therefore be charged to all issuers. In the same way as a seller of a creampuff only can sell his car for the price of a lemon, a low-risk issuer has to pay the same rate of interest as a high-risk borrower. Consequently, in the same way that asymmetric information leads to a withdrawal of creampuffs in the used-car market, a high rate of interest results in the removal of good risks on the credit market. Economic output on the credit market becomes suboptimal because lenders misallocate their productive resources. Although a potential bondholder has a certain ability to distinguish between high-risk and low-risk borrowers, inevitably a lender will make a mistake. As the rating scale suggests, the riskiness of an issuer cannot be classified into only two categories. Enter credit ratings.

By providing information at the intersection between borrowers and lenders, rating agencies satisfy the needs on both the demand and the supply side of the credit market (Langohr & Langohr, 2011).

For the demand side, a credit rating reduces the cost of information. Market participants do not possess the time, ability, nor the resources needed to adequately assess credit risk conveyed in public and nonpublic information. By taking into account a credit rating as an independent second opinion, the ability to distinguish creampuffs from lemons is significantly improved. In terms of economic output, optimal investment decisions are facilitated because credit ratings help creditors to allocate their capital in a more productive way.

For the supply side, obtaining a rating is a 'credit passport' that reduces the cost of accessing the credit market (Moody's 2014). As Table 2.2 highlights, this is because credit ratings and credit spreads in general are negatively correlated. By signaling that it is not a 'lemon', an issuer can spend less on interest payments by paying a lower yield. By achieving a lower cost of borrowing through a tighter credit spread, a credit rating can for that reason also be seen as a source of competition.

2.4. Moody's credit rating scale

Moody's position the creditworthiness of an issuer on an ordinal credit rating scale that is depicted in Table 2.4. The ordinality implies that all ratings along the scale are comparable: the higher the rating, the lower is the historically observed default rate. However, the scale is not an absolute measure. Although the scale indicates that firms with a Ba rating are more likely to default than A-rated firms and less likely to default than Ca-rated firms, the scale does not reveal how much more or how much less the firm is likely to default. The scale does neither define the absolute default probability of an A, Ba or Ca rated issuer. It is in this sense that rating scales are ordinal.

Companies rated Baa or above are regarded as investment grade. Institutional investors and other risk-averse investors predominantly hold these bonds, either by internal or external regulations. Companies that are rated below Baa are regarded as speculative grade or high yield. Speculative bonds appeal to risk-seeking investors pursuing high returns.

Table 2.4 – *Moody's Global Long-Term Rating Scale*

Aaa	Obligations rated Aaa are judged to be of the highest quality, subject to the lowest level of credit risk.
Aa	Obligations rated Aa are judged to be of high quality and are subject to very low credit risk.
A	Obligations rated A are judged to be upper-medium grade and are subject to low credit risk.
Baa	Obligations rated Baa are judged to be medium-grade and subject to moderate credit risk and as such may possess certain speculative characteristics.
Ba	Obligations rated Ba are judged to be medium-grade and subject to substantial credit risk.
B	Obligations rated B are considered speculative and are subject to high credit risk.
Caa	Obligations rated Caa are judged to be speculative of poor standing and are subject to very high credit risk.
Ca	Obligations rated Ca are highly speculative and are likely in, or very near, default, with some prospects of recovery of principal and interest.
C	Obligations rated C are the lowest rated and are typically in default, with little prospect for recovery of principal or interest.

2.5. Moody's rating methodology

Moody's describe their credit ratings as forward-looking opinions about the creditworthiness of an issuer (Moody's 2014). The agency computes various financial ratios and tracks them over time in order to analyze the financial strength of an issuer. Moody's emphasizes the importance of qualitative aspects by stating that although quantification is an integral part of their analysis, it is only a part of their overall approach (Caouette, JB, Altman, EI, & Narayanan, P 2008**)**. By analyzing the strengths and weaknesses of an issuer in comparison to its worldwide peers, and by examining external aspects such as industry- and country-level trends, the primary focus of the analysis is the ability of an issuer to generate future cash flows (Moody's 2014).

Moody's is rather vague when describing its rating methodology. The agency explains that its methodology is based on two fundamental questions:

1. What is the risk to the debt holder of not receiving timely payment of principal and interest on this specific debt security?
2. How does the level of risk compare with that of all other debt securities?

Although several analytical principles are said to guide the rating methodology, only two are exemplified. The first principle is the importance of a long-term focus. In order to "rate through the cycle", i.e. not allowing credit ratings to reflect short-term market movements, the analysis is focused on the fundamental factors that drives an issuer's long-term ability to meet debt payments. Examples such as major economic downturns, radical changes in management strategy and major regulatory developments are given (Moody's 2014). The second principle is the "emphasis on stability and predictability of cash flow". Moody's (2014) state that the main purpose of their analysis is to understand the drivers of cash flow in general and the predictability and sustainability of it in particular. The agency is not more precise than that, but mentions that the specific risk factors differ substantially depending on the industry.

2.6. Moody's rating process

The rating process begins with a meeting between a lead analyst and the management of the issuing company (Moody's 2014). At the meeting, topics such as industry trends, management quality and its attitude towards risk-taking, corporate strategy, debt structure, financial position, and sources of liquidity are discussed in detail (Moody's 2014). The issuer also provides the analyst with detailed information regarding future projections and various internal reports. The purpose of the meeting is to review credit factors such as key financing and operating plans. Facility tours might also be carried out to provide a better understanding of the issuer's business (Rachev & Trueck 2009).

Based upon this, the analyst conducts a first assessment of the issuer's risk profile. In most cases, further meetings are arranged in order to obtain additional information and possible clarification. Once the analysis is completed, the analyst makes a recommendation to the rating committee. This is the second part of the rating process.

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When presenting the rating suggestion to the rating committee, it is the responsibility of the lead analyst to make certain that all the relevant issues underlying the rating are covered and discussed in detail (Moody's 2014). In order to overcome the subjective nature of the analysis put forth by the analyst, the purpose of the committee is to provide an objective opinion to the rating process.

The rating process is guided by a common set of basic analytical principles and lasts approximately four weeks. These include an evaluation of financial risk, an emphasis on qualitative factors such as the nature of an issuer's business and operating environment, and a long-term focus. Discussions during the rating committee meeting are highly confidential, and only analysts from Moody's are allowed to attend them. Once the rating decision has been made, the issuer is allowed to respond to it by providing additional data before a public release of the rating is published (Moody's 2014).

3. Previous Research

The finance literature contains a vast amount of academic papers that try to predict credit ratings or corporate bankruptcies by means of financial variables. This chapter covers the most relevant. The purpose is two-fold: to distinguish the financial variables that are most likely to affect a firm's credit rating, and to identify the most suitable statistical technique for developing the replicating credit rating models.

One of the most influential papers on corporate credit analysis dates back almost half a century ago. In 1968, Edward Altman pioneered the use of financial ratios to predict corporate bankruptcy by developing what has become known as the Z-score model. By applying a technique known as discriminant analysis, Altman attempted to predict whether a firm would go into bankruptcy within one to five years. Based on a sample of 66 publicly traded manufacturing firms, Altman identified five financial ratios that formed the basis of the Z-score model. In 94% of the cases, Altman's Z-score model proved to be accurate in predicting corporate bankruptcy.

Equation 3.1 – *Altman's Z-score model*

$$Z = 1.2\frac{\text{Working Capital}}{\text{Total Assets}} + 1.4\frac{\text{Retained Earnings}}{\text{Total Assets}} + 3.3\frac{\text{EBIT}}{\text{Total Assets}} + 0.6\frac{\text{Market Value Equity}}{\text{Total Liabilities}} + 1.0\frac{\text{Sales}}{\text{Total Assets}}$$

Pinches & Mingo (1973) were among the first to use financial variables in order to develop a model for predicting credit ratings. By applying a multiple discriminant model (MDA-model), they took a hitherto new approach in explaining credit ratings by means of financial data. Pinches & Mingo (1973) argued that the MDA-model was superior to earlier models because the dependent variables assumed discrete values, which the authors claimed was the case with credit ratings. Based on an original group of 35 variables, Pinches and Mingo (1973) found that the most accurate replicating credit rating model was developed when variables related to earnings stability, size, seniority of debt, financial leverage, return on investment, and interest coverage were considered. The MDA-model correctly predicted 70% of the in-sample ratings and 60% of the out-of-sample ratings. It could, however, only predict the rating category Baa 1 out of 25 times. Otherwise, the model only failed to predict 2 out of 132 ratings when a margin of error corresponding to one credit rating was accepted. Hence, Pinches and Mingo's (1973) model could fairly well predict four of the five credit rating categories considered.

Kaplan & Urwitz (1979) criticized the MDA-model proposed by Pinches & Mingo (1973) for not accounting for the ordinality of the credit rating scale. According to Kaplan & Urwitz (1979), the method incorrectly assumed that ratings are measured on an interval scale where the distance in terms of risk is the same between all the rating categories. To remedy the problems, Kaplan & Urwitz (1979) applied the maximum likelihood method and proposed an ordered probit model to calculate the values of the independent variables. They considered this method to be more accurate than the least squares method applied by Pinches & Mingo. The authors found that seniority of debt, company size, return on assets, and long-term debt to equity were the most significant variables in explaining a credit rating (Kaplan & Urwitz 1979). The interest coverage ratio and measures of liquidity were found to be non-significant. The explanatory power of their model was just under 60%.

One of the first attempts to estimate the probability of bankruptcy by applying a logit model was carried out by Ohlson (1980). A logit regression is an alternative method to the multiple discriminant analysis and has the advantage of estimating probabilities – in this case the probability of bankruptcy. With a prediction rate of 96%, Ohlson identified the following set of financial variables as the best indicators of the probability of default: size, total liabilities to total assets, net income to total assets, and current assets to current liabilities.

Building upon the advantages of logit models, Resti (2002) argued that multivariate models could be used to extract some constant patterns from agency ratings that could be used as guidelines when evaluating unrated firms. In contrast to most of the previous research, Resti (2002) attempted to replicate Moody's ratings by only using European data. To make the data more robust, Resti (2002) collected financial information from a three-year period. Based upon 184 issuers in 16 countries, the following variables were identified as key drivers of agency ratings: profit margin, cash cycle, size, total debt to total assets, profit volatility, and a binary variable indicating whether a firm was state-owned or not. However, as the percentage of discordant pairs (17%) was far from negligible, Resti concluded that statistical models must be complemented by human judgment in order to mimic the work of professional rating agencies as closely as possible.

For the purpose of this thesis, a second key conclusion from the work of Resti (2002) was that industry sectors play a significant role in shaping the credit rating of an issuer. By highlighting that operating revenues had a different impact on manufacturing and service firms, Resti (2002) suggested that financial variables must be evaluated in different ways depending on the industry sector. However, Resti (2002) was unable to compute an industry-specific model with his sample as the number of rated European firms was rather small, especially in comparison to the United States.

Additional work on replicating credit rating models by means of financial variables was carried out by Gray, Mirkovic & Ragunathan (2006). The authors applied an ordered probit model in order to examine credit ratings assigned by S&P to Australian issuers. Based upon 392 observations between 1995-2002, the authors found that interest coverage variables, profitability variables, industry concentration, and long-term debt had the most profound effect on credit ratings. Cash-flow ratios and total debt were not significant financial variables in their study. On the contrary, the significance of the two leverage ratios differed considerably. While their ordered probit model had an overall success rate of 62%, it could not discriminate the highest rating categories. All firms that were rated A and above appeared similar in relation to the financial ratios and industry variables that the authors examined.

A more recent study on replicating rating models was conducted by Amdouni & Soumaré (2013). Their purpose was to identify quantitative variables that could explain the ratings assigned to Canadian firms by S&P. Amdouni & Soumaré (2013) approached the subject by initially proposing a two-class model that classified issuers into two categories: investment grade and speculative grade. Thereafter, a more detailed model was developed that accounted for all the grading scales.

The multivariate logit model proposed by the authors identified the following financial variables as the ones with highest explanatory power: leverage, liquidity, size, profitability, earnings volatility and dividend payments. The in-sample forecasts lead to concordant rates of 88% for the two-class model and 71% for the extended model. The out-of-sample forecasts lead to concordant rates of 86% and 61% respectively. Given the high prediction error, the authors concluded that the prediction rate could be greatly enhanced once the number of rated firms in Canada increases. Until then, quantitative models should be complemented with qualitative analyses produced by financial analysts.

Table 3.1 – *Summary of previous research*

Authors (Year)	Method	Data collection	Most significant ratio category	Accuracy (%)
Altman (1968)	MDA	United States	See Equation 3.1	94%
Pinches & Mingo (1973)	MDA	United States	Earnings volatility, interest coverage, leverage, profitability, size	70%
Kaplan & Urwitz (1979)	Ordered Probit Model	United States	Leverage, profitability, seniority, size	60%
Ohlson (1980)	Logit Model	United States	Size, leverage, profitability, liquidity	96%
Resti (2002)	Multivariate Logit Model	Europe	Cash-flow, earnings volatility, leverage, profitability, size, state-owned dummy	83%
Gray, Mirkovic & Ragunathan (2006)	Ordered Probit Model	Australia	Industry concentration, interest coverage, leverage, profitability	62%
Amdouni & Soumaré (2013)	Multivariate Logit Model	Canada	Leverage, liquidity, size, profitability, earnings volatility, dividend payments	88% / 71%

4. Financial Ratio Analysis

Previous research suggests that there are a lot of financial ratios that can be used to construct a replicating credit rating model. Many of these resemble each other, and five categories of financial variables stand out for having consistently proved significant in explaining credit ratings or predicting default: profitability, liquidity, interest coverage, leverage and size. Since they all provide a distinct understanding about creditworthiness, the following section will discuss each category in more detail. Table 6.1 provides an overview of all the financial variables in each profile group that will be tested when developing the models.

4.1. Profitability

Ceteris paribus, the higher the profitability, the lower is the probability of default (Falkenstein 2002). The future existence of a firm revolves around its ability to generate profit, and all the previous papers accounted for some kind of profitability measure. The usefulness of profitability measures depends on the purpose of the analysis. Managers might analyze profit margins in order to evaluate the efficiency of their businesses, while investors are more interested in comparing returns on equity when deciding upon capital investments. Since bondholders receive a fixed payment regardless of the level of profitability, their primary concern is the stability of profits. Bonds have in general a long term to maturity, and bondholders must be attentive to profitability measures as their returns depend on the issuer's ability to generate future earnings and as such service debt repayments (ed. Collett & Schell 1996). Profitability ratios are also called performance ratios, and they are typically subdivided into margins and returns.

Profitability margins are all variations on a similar theme. Profits are sales that trickle down along the various classes of expenses, and by comparing e.g. gross profit, EBITDA, EBIT, EBT and net profit to total revenue, the common purpose is to evaluate the ability to control costs. Margin analysis is carried out at several levels as each ratio provides distinct information regarding this ability. Profitability returns, on the other hand, compare profits to the base of wealth required to create the profits. By analyzing how profits compare with assets, equity, capital, and invested capital, the purpose is to determine the efficiency of using wealth in order to generate earnings.

4.2. Liquidity

Liquidity is the ability to turn operating assets into cash (ed. Collett & Schell 1996). It is central in the assessment of credit risk, since an illiquid firm is neither able to pay its creditors nor carry out profitable investments. Its importance is reflected in the second principle of Moody's rating methodology, which emphasizes the stability and predictability of cash flow. Liquidity risk is divided into short-term and long-term analysis, and both perspectives provide valuable insights when assessing a company's credit risk.

The current ratio is the most basic measure of short-term liquidity risk and describes the ability to meet short-term liabilities with short-term assets. It is suggested that a current ratio above 2.0 is a sign of low short-term liquidity risk, but applying such a general rule of thumb is unwise because the ratio is highly industry specific. The quick ratio is a more conservative version that only includes the most liquid current assets. The cash ratio is even narrower as it measures the ability to repay current liabilities by only using cash and cash equivalents. The cash flow from operations (CFO) to short-term debt ratio avoids the convertibility-to-cash problem by using actual cash flows generated from operations rather than current and potential cash flow resources.

Long-term liquidity risk provides an overview of a firm's long-term financial health and its ability to satisfy future obligations. Long-term liquidity ratios include but are not limited to the CFO to debt ratio and the capital expenditure ratio. The CFO to debt ratio is almost identical to the CFO to short-term debt ratio, wherein the difference lies in that the former includes all non-current liabilities. The capital expenditure ratio shows the extent to which a company's capital expenditure can be funded through the cash flows generated from its operations.

The interpretation of liquidity is ambiguous and should be used with caution on a standalone basis. The 'liquidity puzzle' that Resti (2002) came across suggests that illiquidity does not necessarily translate into higher risk. On the contrary, and as the pecking-order theory supports, low liquidity may be a sign of good management, while high liquidity may suggest sub-optimal use of capital.

4.3. Interest coverage

Interest coverage comprises a set of financial ratios that measures long-term liquidity risk. What distinguishes interest coverage ratios from liquidity ratios is that they measure the ability to meet financial expenses over time. In other words, they provide an indication of how vulnerable a company is in relation to its interest payments. Recalling that Moody's rating methodology is based upon "the risk to the debt holder of not receiving timely payment of principal and interest", the long-term ability to service debt is of crucial importance for creditors. The most recognized metric that provides this indication is the interest coverage ratio. The ratio indicates how many times operating profit covers net financial expenses. Given that interest payments are the bread and butter of bonds, several variations of this ratio will be included in the model development process.

4.4. Leverage

Financial leverage describes the capital structure of a firm and indicates its debt capacity. Although higher leverage implies a higher probability of default, it is difficult to determine how much leverage is too much, as it depends on the industry. In addition, the ability of servicing debt does not depend on the debt itself, but rather the reliability of future earnings and cash flow. Increasing debt over equity is in some cases even favorable. It may decrease the overall cost of capital since debt is cheaper than equity, and it may enhance profitability because interest is tax deductible. Nevertheless, highly leveraged firms have a smaller cushion to unanticipated events, and higher leveraged firms in general have lower credit ratings. It is usually not possible to know which debt measure is preferable when evaluating a firm's creditworthiness in terms of leverage measures. Some advocate that all debts should be evaluated, while others, including Gray et al, argue that it is sufficient to only include long-term debt (Brealey et al. 2008; Gray et al 2006).

4.5. Size

Although size is not a financial ratio *per se*, the majority of the previous studies found it to be a significant variable when constructing models that replicate credit ratings. The principal argument put forth is that larger companies in general are more diversified in their exposure to market risk. A second argument is that large firms are more reliable and comprehensive than smaller firms in the way they disclose corporate information (Resti 2002). Adams et al (2003) also point out that larger firms more often have access to leading expertise, which can be beneficial from a risk standpoint.

5. Industry Analysis

In essence, creating a replicating credit rating model is merely a quantitative procedure. It is a matter of deciding upon a statistical processing technique, inserting a wide range of variables in a statistical program and eventually discovering which ones provide the best outcome. However, this approach does not provide an understanding to why certain variables prove significant in one model but maybe not the other. The statistical outcome must be complemented with a theoretical explanation. Understanding the industry might explain the cause and effect relationship, and provide the story that gives the model a meaning.

Porter's Five Forces is the centerpiece of industry analysis. It is a simple but powerful tool that frames the structure of an industry (Porter 2008). The point of the framework is not to decide whether an industry is attractive or not, but rather to understand its fundamental structure. The framework includes three 'horizontal' forces of competition: threat of new entrants, threat of substitutes, and the degree of rivalry. It also includes two 'vertical' types of competition: the power of buyers and the power of suppliers. Together, these five forces shape the nature of the competition within an industry (Porter 2008). In this section, Porter's Five Forces will be applied on the oil & gas and consumer products industry respectively to highlight their similarities and differences. Firstly, a brief overview of each industry is given. Thereafter, each of the five forces is discussed.

5.1. Oil & Gas

The oil & gas industry is one of the largest industries in the world, and the United States accounts for 20% of the global oil & gas market value (Inkpen & Moffett 2011). Its magnitude is reflected in the Fortune 500 list, where five companies including Royal Dutch Shell (2nd), ExxonMobil (5th) and BP (6th) reached the top ten in 2014 (Fortune 2014)[2]. It is also among the most important in the world. It has the ability to influence national security, elections, geopolitics, international conflicts, and the everyday life of almost everyone (Inkpen & Moffett 2011).

[2] The Fortune 500 is an annual ranking of the top 500 corporations worldwide as measured by revenue.

The oil & gas industry is rather cyclical. The industry beta is 1.34, which means that the industry is sensitive to market movements and is exposed to higher market risk (Reuters 2015). The industry is moreover highly capital-intensive, and market participants often depend on external debt in order to either carry out these activities or to finance mergers and acquisitions.

Few industries are as complex as oil & gas. It includes upstream activities such as exploration, development and production; midstream activities like trading and transportation; and downstream activities involving oil refining and marketing (Inkpen & Moffett 2011). The purpose of this section is to provide an overall understanding about the industry, and therefore such strategic group analysis is not accounted for.

Recent Developments

Well into the writing of this thesis, several events reshaped the oil & gas industry. The shale oil discovery in North America combined with slow growth in energy-intensive countries such as China put significant pressure on market participants and triggered a crisis in the oil & gas industry. As the price of crude oil plummeted from $115 per barrel in June to $49 in January 2015, OPEC lowered its forecast for oil demand in 2015 to 28.9 million barrels a day (its lowest level since 2002) and the number of U.S. oilrigs in operation fell to its lowest number since May 2009. These recent developments in the industry are abstracted from in this thesis. All ratings accounted for were assigned before the Oil Crisis broke out and any possible rating downgrades are disregarded.

The power of buyers

Oil and gas are commodities that are priced by the forces of supply and demand and traded on the mercantile exchanges. The limited ability to pass on costs to customers makes the companies price takers, and the industry is therefore highly exposed to commodity price risk. Oil and gas are also virtually indistinguishable commodities. Standardized and undifferentiated products allow buyers to play industry participants off against one another (Porter 2008). The power of buyers is therefore strong. Cost advantages in terms of economies of scale and optimization of invested capital are key success factors to counter the force and achieve competitive advantage (ed. Grant 2010).

The power of suppliers

Three circumstances within the oil & gas industry are consistent with Porter's description of what characterizes an industry with high supplier power: the existence of the OPEC, asset specific investments, and political instability.

Porter (2008) argues that powerful suppliers can affect the market by either charging higher prices or by limiting production. The creation of the OPEC in 1960 was a game-changer that switched the bargaining power from the large oil companies to the producing countries. The Oil Crisis of 1973-1974 is perhaps the best example of their power: the proclaimed oil embargo only lasted for a few months, but the price of oil increased from $2.7 to $11.2 per barrel (Backus & Crucini 1998). The OPEC still has a strong influence on the price of oil as it controls around 40% of the world's supply through its oil mining and extraction firms (Hokroh 2014).

Porter (2008) also points out that high switching costs makes it difficult for industry participants to play suppliers of against each other. This is certainly the case in the oil & gas industry due to its high asset specificity. Investments in e.g. drilling rigs are impossible or extremely expensive to relocate due to their site specificity.

Oil and gas is commonly supplied from politically insecure countries. Political instability increases the power of suppliers since assets can be confiscated at any time. This occurred in 2007 when Venezuela seized one of ExxonMobil's projects. Although the company was re-compensated with $1.6 billion recently, it was nevertheless a fraction of the demanded amount (Bloomberg 2014).

Threat of entrants

The market participants are large, long-established and diversified multinational companies. By using their large scale of operations in e.g. oil exploration, production, refining and transportation, incumbents exploit supply-side economies of scale that allows them to reduce costs and enhance profitability. Bearing in mind the power of buyers, this is crucial in an industry where the participants are price takers. Entering the market therefore requires significant up-front investments to set up fixed facilities such as drilling rigs. Besides financing on-going projects and operations, capital is also required for unrecoverable expenditures in research and development in order to gain exploration and extraction capabilities. According to Porter (2008), barriers to entry are especially high in such circumstances.

Moreover, Porter (2008) argues that restrictive government policies limits entry into industries. Extraction of oil & gas requires a permission that is given by national governments, and acquiring such permission is usually a drawn-out process (Inkpen & Moffett 2011). Hence, because of economies of scale, significant up-front and on-going capital requirements, and restrictive government policy, the threat of new entrants is low.

Threat of substitutes

In pace with the rising awareness concerning climate change, renewable energy such as solar and wind power has gained increased attention. These alternative energy sources offer significant benefits in respect to sustainability. It is likely that these will occupy a greater share of the energy market in the long-term as the oil and gas reserves are expected to decline in the future.

However, the shift to green energy is both a costly and lengthy process and most industries rely heavily on oil and gas. A complete transition would require high switching costs, which makes complete substitution unlikely (Inkpen & Moffett 2011). Since there are few substitutes that are commercially feasible today, the threat of substitutes is low. This is consistent with Porter (2008), who argues that the threat of substitutes is low when buyers' cost of switching to substitutes is high.

Degree of rivalry

Oil & gas companies are relatively equal in size and power; they are typically large and integrated companies that exploit the scale of their operations (Inkpen & Moffen 2011). The presence of equal incumbents increases the intensity of rivalry in an industry (Porter 2008). The degree of rivalry is also intensified due to the commodity-based nature of the industry where competitive advantage primarily is achieved through operational efficiency and cost advantages.

Furthermore, the oil & gas industry is a capital-intensive industry with high fixed costs (Inkpen & Moffett 2011). Asset specificity makes it hard to exit the market because of opportunity costs. In addition, Porter (2008) argues that slowdown in production precipitates fights for market shares that increases the degree of rivalry. This argument is applicable on the oil & gas industry as it is experiencing declining reserves.

5.2. Consumer Products

Consumer products are tangible goods purchased by households for daily and non-business purposes. Marketing is crucial in the industry where individual consumers constitute the bulk of the customer base. The industry is the foundation of the modern consumer economy and the production and sale of consumer products make up a large portion of U.S. GDP and employment. The industry beta is 0.48 (Reuters 2015), which means that the industry is non-cyclical and insensitive to market movements.

Consumer products are a broad category of mass-market items and include many sub-sectors. Moody's (2014) divides the industry into e.g. alcoholic beverages (such as Anheuser-Busch), apparel & shoes (Nike), soft beverages (PepsiCo), household & personal care (Colgate-Palmolive), packaged food (Unilever), and tobacco (British American Tobacco). The purpose of this section is to provide an overall understanding about the competitive forces of the industry, and therefore the five forces will be applied on the consumer products industry in general.

Threat of entrants

The key feature of consumer products is their differentiable characteristics. Long-established companies have the advantage to exploit brand awareness and customer loyalty.

In terms of brand awareness, new entrants have to invest heavily on advertising and promotion in order to gain recognition similar to the established firms. In comparison to early entrants, late entrants in the consumer products industry incur an additional advertising and promotional cost amounting to more than 2% of sales revenue (ed. Grant 2010, p.72). In terms of customer loyalty, the percentage of faithful clients is high in the consumer products industry; 61% of U.S. customers are loyal to a single brand in toothpastes, 65% in mayonnaise, and 71% in tobacco (ed. Grant 2010, p.72).

Furthermore, supermarkets have limited shelf space and competition for this space is strong among already-established firms. Retailers might be reluctant to sell products from unknown firms, and therefore brand recognition and customer loyalty also forms a barrier to accessing distribution channels. Although the Internet has allowed entrants to partly circumvent the distribution barriers, the overall threat of new entrants in the consumer products industry is considered to be fairly low.

The power of buyers

The larger the number of buyers and the smaller their purchases, the lower are the costs of losing one (ed. Grant 2010). The industry contains many small-size customers, and customers have a weak ability to influence the price due to this fragmentation. Customers are also less price-sensitive since consumer products are differentiated. For these two reasons, the power of buyers is weak.

The power of suppliers

Since 1972, companies must adhere to the 'Consumer Product Safety Act' (CPSA 2015). Firms must cope with the established safety standards and their products can be recalled if they present substantial risks of injury. Bearing in mind the importance of brand reputation, such a scenario would be devastating for firms operating in the consumer products industry. This places stringent requirements on their suppliers and the cost of switching suppliers is high and time consuming.

However, switching costs are far from as high as in the oil & gas industry. Neither the uniqueness nor the scarcity of the resources supplied to the manufacturing of consumer products is comparable to oil or gas. Suppliers are also dependent on reputable customers like Nike, Pepsi or Unilever in order to generate revenues. In terms of supplier power in the consumer products industry, there is as such a mutual dependent relationship. The power of suppliers is therefore considered to be limited.

Threat of substitutes

Buyers of consumer products do not face any fixed costs when substituting suppliers. The switching costs are nonexistent, and substitute goods such as cheaper store-branded products can erode the pricing power of branding and differentiation. By and large, the threat of substitutes thus boils down to the taste and preference of each individual customer. Some (including the author of this thesis) might argue that a shampoo is a shampoo, irrespective of the brand as all products fulfill the main purpose of washing ones hair. Others (including the author of this thesis) certainly would disagree to apply the same line of argument when it comes to beers.

Many firms manufacture these store-branded products. By offering a lower-price alternative by themselves, these firms partly overcome the issue of losing sales to private-label competitors. Hence, the threat of substitutes is high, but not necessarily bad.

Degree of rivalry

The consumer products industry is a mature sector, and competition is in general intense in stagnating markets. As previously mentioned, there is a ferocious competition for shelf space at supermarkets among already-established firms. Although the existence of product differentiation and brand loyalty decreases the intensity of price competition, the cost of switching between two brands is low – a customer does not incur any costs for buying one brand of detergent instead of another. The degree of rivalry is therefore high.

Table 5.2 – *A Summary of the Porter's Five Forces Analysis*

	Oil & Gas	Consumer Products
Power of buyers	High	Low
Power of suppliers	High	Moderate
Threat of entrants	Low	Low
Threat of substitutes	Low	High
Degree of rivalry	High	High

6. Model Development

The statistical models presented in Table 3.1 are all variations on a similar theme; they all include a combination of quantifiable financial variables that either aim to replicate credit ratings or predict corporate defaults. Both logit and probit models are appropriate in the former case where the dependent variable has more than two categories. In contrast to the MDA-model that assumes the dependent variable to be nominal, logit and probit models do not make as strong assumptions because of its ordinal and conditional nature. Both logit and probit models are nowadays preferred as most statistical software contains these algorithms.

However, logistic regression is considered as the technique with the highest predictive power for forecasting credit ratings (Wiginton 1980). It is also reported as a widely used technique under the regulatory framework (Basel Committee on Banking Supervision 2000).

As originally suggested by Kaplan and Urwitz (1977), the statistical method applied to develop the replicating rating models is therefore the multivariate logit model, where the dependent variable is the rating while the financial ratios represent the independent and explanatory variables. A step-by-step description of the model development is provided in the following sub-sections of this chapter.

Following Resti's (2002) recommendation, three years of financial data is collected for each rated company in order to make the data more robust. In line with Moody's rating methodology, this way of collecting data provides a way of "rating through the cycle" where the credit ratings do not reflect short-term market movements. Bearing in mind the problems Gray et al (2006) had with distinguishing firms within the highest rating categories, and in order to have a sufficient number of observations in each rating category to make the statistical tests more reliable, companies rated Aaa, Aa and A are merged into one rating category. For the same reason, intermediate notches (e.g. Aa1 or Baa3) are excluded. The model will thus include four categories: Aaa/Aa/A, Baa, Ba, and B.

Previous research has suggested various financial ratios as key variables that explain credit ratings. The disparity indicates that it is not possible to determine which ratios always are the best ones at predicting credit ratings. However, certain categories of financial ratios recur consistently, and for this reason a wide range of financial ratios within these categories are tested. Table 6 on the following page groups these financial variables according to their respective category.

Table 6 – *Financial variable selection*

Category	Financial ratio	Previous research
Profitability	Return on assets	Kaplan & Urwitz (1979), Ohlson 1980)
	Return on capital	-
	Return on equity	-
	Return on invested capital	-
	EBITDA margin	-
	Gross margin	-
	Income before XO margin	-
	Incremental operating margin	-
	Net Income to common margin	-
	Operating margin	Gray, Mirkovic & Ragunathan (2006)
	Pretax profit margin	-
	Profit margin	Resti (2002), Amdouni & Soumaré (2013)
Leverage	Common equity to total assets	-
	Long-term debt to equity	Kaplan & Urwitz (1979)
	Long-term debt to capital	-
	Long-term debt to total assets	Pinches & Mingo (1973), Gray et al (2006)
	Total debt to equity	Amdouni & Soumaré (2013)
	Total debt to capital	-
	Total debt to total assets	Ohlson (1980), Resti (2002)
	Net debt to equity	-
	Net debt to capital	-
	Total debt to EBITDA	Amdouni & Soumaré (2013)
	Net debt to EBITDA	-
	Total debt to EBIT	Gray, Mirkovic & Ragunathan (2006)
	Net debt to EBIT	-
Liquidity	Cash ratio	Resti (2002)
	Current ratio	Amdouni & Soumaré (2013)
	Quick ratio	-
	CFO to short-term debt ratio	Amdouni & Soumaré (2013)
	CFO to debt ratio	Ohlson (1980)
Interest coverage	EBITDA to interest expense	-
	(EBITDA-CapEx) to interest expense	-
	EBIT to interest expense	Gray, Mirkovic & Ragunathan (2006)
	EBITDA to cash interest paid	-
	(EBITDA-CapEx) to cash interest paid	-
	EBIT to cash interest paid	-
Size	EBITDA	Resti (2002)
	EBIT	-
	EBITDA-CapEx	-
	Total assets	Kaplan & Urwitz (1979), Ohlson (1980)
	Total equity	-
	Total debt	-
Other	Altman's Z-score	Altman (1968)

6.1. Descriptive statistics

Initially, basic descriptive statistics are calculated for all variables listed in Table 6. This is done on the whole data sample, irrespective of industry. A Kolmogorov-Smirnov test is included to assess the normal distribution and determine the suitability of a parametric test. A failure analysis that specifies for what reasons certain issuers are removed from the data sample concludes the first step.

6.2. Univariate analysis – initial selection of variables

In the univariate analysis, the data sample is divided per industry. The purpose of the univariate analysis is to identify the financial variables that on a stand-alone basis provide significant predictive power for estimating credit ratings. By means of analysis of variance (ANOVA), the intention is to single out the variables whose significance level is $p < 0.05$, as this limit is generally considered a yardstick for what levels of performance one is eligible to comment on. The variables are ranked according to their level of significance. This is calculated by Fisher's F-test.

6.3. Multicollinearity analysis – second selection of variables

A problem with logistic regression is that independent variables might be highly correlated with each other. According to Lardaro (1993), this problem of multicollinearity is however nothing unusual when analyzing economic data. On the contrary, it would be unreasonable to expect that independent variables would be entirely isolated from each other, given that they are grouped into categories with similar characteristics. Multicollinearity should rather be seen as a natural part of these tests. Nevertheless, highly correlated variables are undesirable in the final credit model, and the purpose of the multicollinearity analysis is therefore to calculate the correlation between the variables with significant predictive power that have passed the previous step.

Higher ranked variables in the univariate list are preferable as their predictive power is stronger. Therefore, variables that have a very strong positive relationship ($r > 0{,}70$) with variables that are higher ranked in the univariate list are eliminated. The result of the multicollinearity analysis is a set of variables that is used in the multivariate analysis as independent variables. Before entering the final model, however, the relationship between these variables and credit ratings is illustrated and analyzed to ensure that the selected variables have the appropriate financial meaning.

6.4. Multivariate analysis – final selection of variables

Although an independent variable might show significant predictive power on a stand-alone basis based on the results of the univariate analysis, its significance might decrease once examined with other independent variables. By means of the so-called 'enter method'; all independent variables are entered into the equation simultaneously. Each variable is evaluated as if it was included in the model after all other variables. The evaluation is based on its contribution to the already-existing model and the divergence from the variables already entered in the model. The enter method is appropriate when the best independent variables are yet unidentified and when there is a small set of independent variables. That is the reason why the original list of 43 financial variables is narrowed down in the previous two steps.

6.5. Model validation

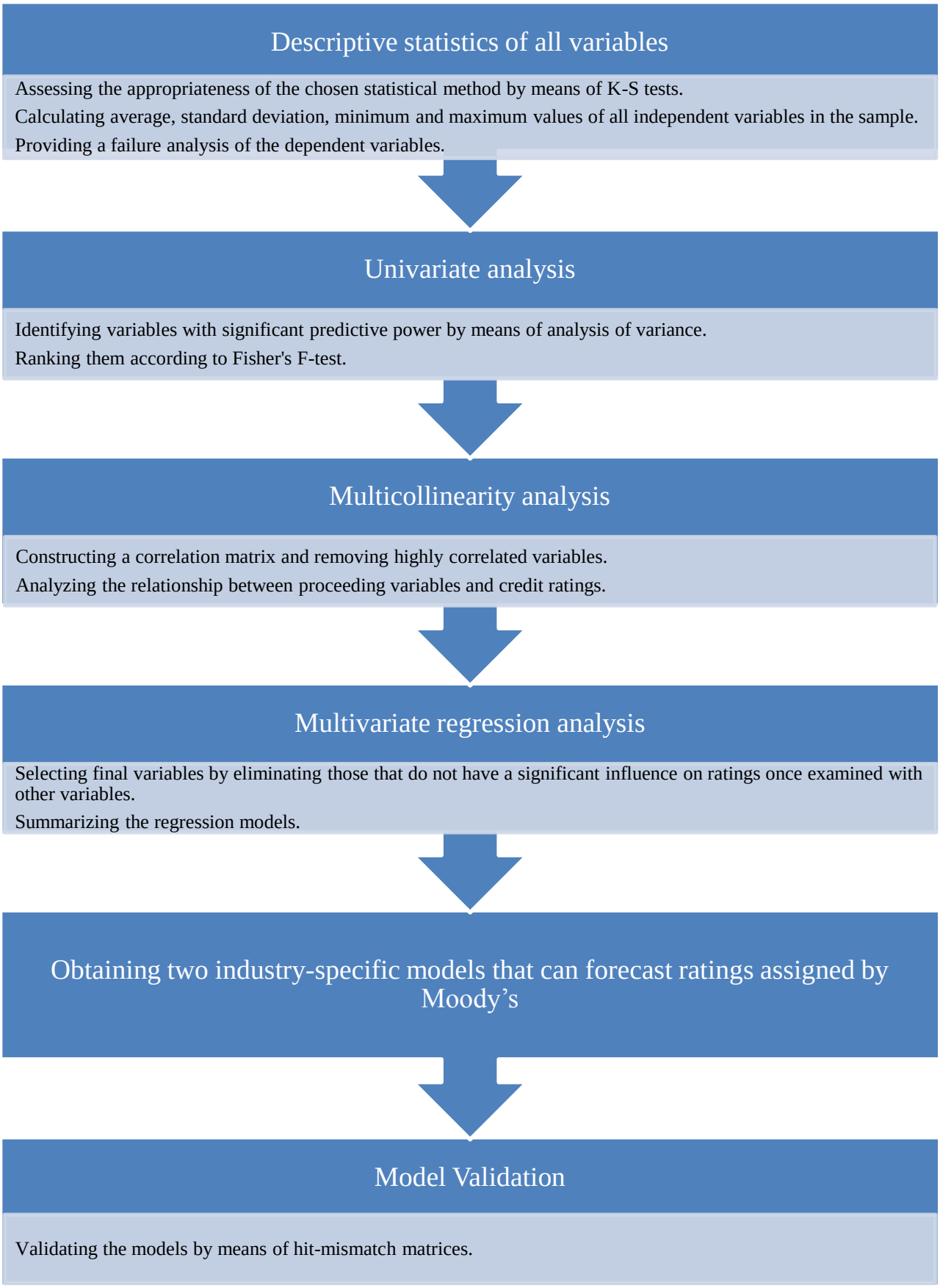
The last step is to validate the final models. In order to have a sufficient number of observations to make the empirical findings more reliable, all available data is used to estimate the industry-specific models. Hence, a major drawback is that there are not enough rated issuers to test the models out of sample. Grün et al (2010) propose a solution to this problem, namely to validate the models by constructing a hit-mismatch matrix. Inspired by Amdouni & Soumaré (2013), the matrix is firstly applied on the whole range of rating categories. Thereafter, the matrix is applied to validate the ability of the models to distinguish investment grade issuers from speculative grade issuers.

6.6. Successive analysis

For the purpose of maintaining a red thread throughout the rest of the thesis, the analysis runs throughout each step of the model development and is successively narrowed down: The univariate step analyzes why certain categories of financial variables are better than others in predicting credit ratings on a standalone basis. The multicollinearity step analyzes the correlation and includes a more in-depth discussion of the relationship between the proceeding financial variables and credit ratings. The multivariate step contains a more thorough analysis of the specific financial variables that are included in the final models. The model validation step concludes the chapter by analyzing why certain models are better than others in predicting credit ratings assigned by Moody's.

As such, it will be possible to answer the research questions and thereby assess the need of industry-specific replicating credit rating models.

Figure 6 – *An overview of the model development*



6.7. Method awareness

The issues of comparison and control are the basis of a good research design. In order to make meaningful and insightful comparisons, one must first decide upon a research design that facilitates the best way of collecting data. The research design must also provide some degree of credibility to the explanations offered in order to achieve control (Bechhofer & Paterson 2000). In quantitative studies, the concepts of validity and reliability specifically relate to data collection, and whether the right kind of data is collected in a reliable manner. The following section will evaluate the validity and reliability of the data collected in this study.

6.7.1. Validity

Two types of data are collected – credit ratings and financial ratios. The credit ratings are set by Moody's and collected from the agency's official website. The financial ratios of the rated firms are collected from the Bloomberg Professional Service at Copenhagen Business School. An attempt to browse through hundreds of annual reports in order to calculate numerous financial ratios is impractical, time consuming and unreliable. Although incomprehensive at times, the Bloomberg Professional Service offers a relatively easy and cheap access to large samples of financial data collected in a highly professional manner. In this way, it is possible to overcome the issue of time constraints while designing a very strong piece of research by using secondary analysis. Hence, with the purpose of creating a model that replicates credit ratings assigned by Moody's by means of financial variables, it is argued that the collected data provides information that is straight to the point. For that reason, the face validity of this study is considered to be high.

Bechhofer & Paterson (2000) describe a good research design as one that provides confidence in the solidity of the conclusion drawn from the data. To achieve this, the authors argue, requires a high degree of control. Bryman (2011) further develops the discussion on the importance of control by arguing that as a control for the author's own impact on the study, it is important to be able to replicate the methodology and provide the same results. If such a replication is not feasible, one can question the validity of the results (Bryman 2011). The credit ratings, the first type of collected data, are set by Moody's and cannot be manipulated. It was found that the financial ratios, the second type of collected data, varied a lot among previous studies. However, the five categories of financial ratios that are tested (profitability, liquidity, interest coverage, leverage, and size) have all proved to be significant in explaining credit ratings in previous research. The fact that these categories recur frequently indicates that they actually measure what they are intended to measure.

Since the selection of the ratio categories is based on credit risk theories and previous research, the possibility that the author's personal values might reduce the validity of the study is minimized. For these reasons, it is argued that the criterion validity of the study is high.

The research design is described as explicitly as possible to enhance the trustworthiness of the study. Matters such as the reasoning behind the multivariate logit model and the steps in the model development have been clarified with the purpose of enhancing the communicative validity.

6.7.2. Reliability

Within quantitative studies, reliability equals reproducibility (Bechhofer & Paterson 2000). In order to facilitate a replicating study on the same data sample, thus increasing the inter-rater reliability of the study, all examined companies are provided in Table 1 and Table 2 in Appendix.

The replicating models are based on companies that provide information on the Bloomberg Professional Service and simultaneously are rated by Moody's. The prospective failure analysis in section 7.1.1 reveals that the shortfall among oil & gas and consumer products firms is quite large (51% and 56% respectively). This limitation reduces the number of usable observations and is a weakness that reduces the reliability of the study; any individual errors, such as mistakes in the data collection, have a greater impact on the outcome than studies that are based on larger data sets.

The replicating rating models have been developed using the statistical software package in SPSS 21 and Microsoft Excel for Mac 2011. Intuitively, this means that the possibility of measurement errors is minimal. If subsequent studies are done on the same data sample, it is likely that the same results will be achieved, which increases the test-retest reliability.

When using secondary data such as academic research it is important to be aware that it has been written with a different research question and purpose than the one put forward in this thesis. Although most of the papers have aimed at creating replicating credit rating models, none has set out to create an industry-specific one. As a screening tool for identifying relevant financial variables and a proper methodology, it is nevertheless argued to be a suitable approach.

7. Results and Analysis

7.1. Descriptive statistics

Table 7.1 presents the number of observations (N), the average values (M), and the standard deviations (SD) of all variables. The K-S test shows that only 8 variables (p>0,05) are not normally distributed. In addition, the samples are large (n>100). For these two reasons it is suitable to apply a parametric test. The selected model is hence appropriate.

Table 7.1 *Descriptive statistics of all financial variables*

Financial variable	N	M	SD	K-S	p
ROE	219	14,6154	28,38782	2,944	0
ROA	225	5,0395	6,43018	0,998	0,272
ROC	206	11,8839	11,21346	2,371	0
ROIC	204	10,5119	14,97858	3,452	0
Gross Margin	222	36,8871	17,29006	0,688	0,731
EBITDA Margin	224	30,7434	22,66707	2,184	0
Operating Margin	225	16,4623	17,20227	1,677	0,007
Incremental Operating Margin	217	-10,5338	275,133	4,908	0
Pretax Margin	225	11,2253	25,17908	2,535	0
Income before XO Margin[3]	225	7,9852	22,69404	2,797	0
Profit Margin	225	8,1642	22,36013	2,732	0
Net Income to Common Margin	225	7,2281	21,71839	2,683	0
Sustainable Growth Rate	205	12,6918	23,01751	3,254	0
Cash Ratio	223	0,4009	0,79319	4,579	0
Current Ratio	223	1,5394	1,04127	2,245	0
Quick Ratio	223	0,9183	0,8377	2,882	0
CFO to average Current Liabilities[4]	223	1,0017	0,84091	2,201	0
Common Equity to Total Assets	223	39,8848	18,75387	1,042	0,228
Long Term Debt to Equity	220	145,9419	435,00266	5,517	0
Long Term Debt to Capital	224	42,005	23,55299	1,563	0,015
Long Term Debt to Total Assets	224	31,3473	16,97874	0,838	0,484
Total Debt to Equity	220	157,4315	459,71155	5,475	0
Total Debt to Capital	224	45,5065	24,34891	1,294	0,07
Total Debt to Total Assets	224	33,5846	16,8415	0,991	0,279
CFO to Total Liabilities	224	21,8681	14,47327	1,75	0,004
CFO to CapEx[5]	224	3,4963	10,5453	5,543	0
Altman's Z Score	177	3,2597	2,16559	1,287	0,073
Total Debt to EBITDA	222	3,3053	3,63955	2,786	0
Net Debt to EBITDA	222	2,9214	3,57748	2,447	0
Total Debt to EBIT	219	6,1777	8,88911	3,716	0
Net Debt to EBIT	219	5,4017	8,80125	3,386	0
EBITDA to Interest Expense	214	26,6921	154,38637	6,293	0
EBITDA-CapEx to Interest Expense	213	-1,4846	63,0702	5,235	0
EBIT to Interest Expense	213	18,1844	109,49408	6,067	0
EBITDA to Cash Interest Paid	207	23,0608	51,39504	4,671	0
EBITDA-CapEx to Cash Interest Paid	207	-3,1093	82,14347	4,905	0
EBIT to Cash Interest Paid	207	16,4412	41,76818	4,826	0
Net Debt to Equity	219	137,514	448,17495	5,237	0
Net Debt to Capital	223	37,3945	26,30409	0,955	0,321
EBITDA	222	1685,7443	3742,48978	4,776	0
EBITDA-CapEx	221	795,177	2724,01011	4,324	0
EBIT	223	1235,9345	2903,42892	4,718	0
Total Debt	219	30,9582	55,77814	4,043	0
Total Assets	219	120,3868	232,92208	4,472	0
Total Equity	219	89,4287	187,73442	4,554	0

[3] XO = extraordinary items
[4] CFO = cash flow from operations
[5] CapEx = capital expenditures

7.1.1. Failure analysis

Table 7.1.1 presents the failure analysis of the rated firms. The bulk (175) of the total shortfall is made up of issuers that do not provide any information on the Bloomberg Professional Services. 33 firms are excluded from the sample selection because the information they provide on Bloomberg is either insufficient or inadequate. The group "Miscellaneous shortfalls" include 40 firms that are excluded because they are either special purpose vehicles, private firms, firms with duplicate ratings, or firms that only provide quarterly reports.

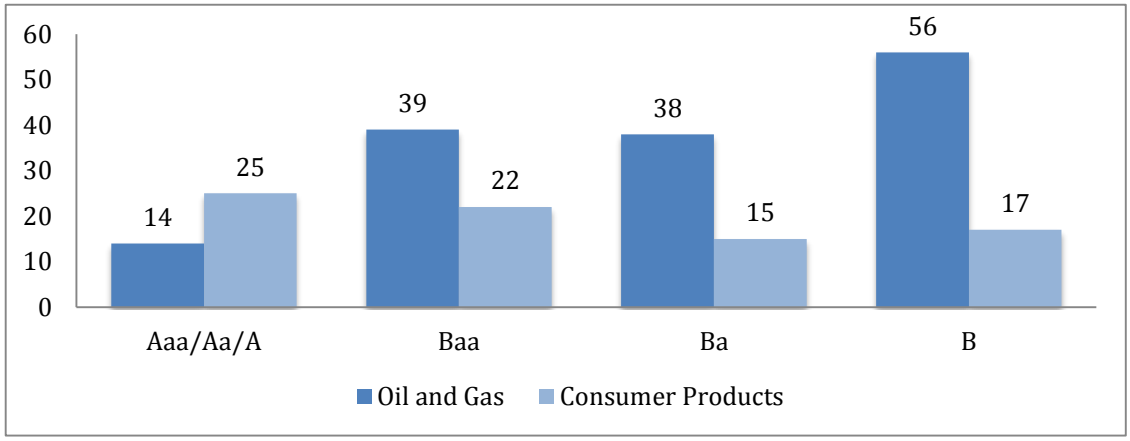
Most of the firms that are rated below B are excluded as they belong to one of the above-mentioned groups. With the benefit of hindsight, the remaining firms that provide sufficient and adequate information on Bloomberg, but are rated below B, have been excluded from the sample in order to have sufficient number of observations in each rating category.

The final samples consist of 147 (65%) issuers in the oil & gas industry and 78 (35%) issuers in the consumer products industry. These are divided into four rating categories, as seen in Figure 7.1.1

Table 7.1.1 *Failure Analysis*

	Oil & Gas	Consumer Products	Total
Number of rated issuers	302	180	482
Issuers without data on BPS	-110 (36%)	-65 (36%)	-175 (36%)
Issuers with insufficient data on BPS	-16 (5%)	-18 (10%)	-33 (7%)
Miscellaneous shortfalls	-24 (8%)	-16 (9%)	-40 (8%)
Issuers rated below B with data on BPS	-5 (2%)	-2 (1%)	-7 (1%)
Final number of issuers	147 (49%)	79 (43%)	226 (47%)

Figure 7.1.1 *Final sample structures by rating classes*



7.2. Univariate analysis

7.2.1. Oil & Gas

Based on the ANOVA results in Table 3 in Appendix, in descending order and on a standalone basis, the following 21 financial variables have a significant predictive power for estimating credit ratings in the oil & gas industry.

Table 7.2.1. *Univariate results in the Oil & Gas industry*

	Financial variable	Ratio Group	F-test	1-pvalue
1	Total Equity	Size	39,824	1,000000
2	Total Assets	Size	37,427	1,000000
3	EBITDA	Size	29,347	1,000000
4	EBIT	Size	25,324	1,000000
5	Total Debt	Size	15,712	1,000000
6	EBITDA-CapEx	Size	14,787	1,000000
7	Long-term Debt to Total Assets	Leverage	8,950	0,999982
8	Long-term Debt to Capital	Leverage	8,886	0,999980
9	Total Debt Total to Assets	Leverage	8,315	0,999961
10	Total Debt to Capital	Leverage	7,754	0,999922
11	Pretax Margin	Profitability	6,555	0,999652
12	Net Income to Common Margin	Profitability	6,195	0,999451
13	Income before XO Margin	Profitability	5,911	0,999214
14	Profit Margin	Profitability	5,431	0,998554
15	Operating Margin	Profitability	5,215	0,998094
16	Return on Assets	Profitability	5,136	0,997887
17	Net Debt to Capital	Leverage	4,937	0,997268
18	Total Debt to EBITDA	Leverage	4,616	0,995881
19	(EBITDA-CapEx) to Cash Interest Paid	Interest coverage	3,946	0,990077
20	Gross Margin	Profitability	3,056	0,969547
21	Net Debt to EBITDA	Leverage	3,024	0,968408

The univariate analysis provides a clear picture of which categories of financial variables are the most significant on a standalone basis. All of the six variables related to size are highest on the univariate list. In consecutive order, the list thereafter consists of four variables related to leverage and six related to profitability. Only one variable that does not relate to these three ratio categories is significant, namely EBITDA-CapEx to cash interest paid.

In terms of size, the Fortune 500 list revealed that the market participants in the oil & gas industry are among the largest corporations in the world. The Five Forces analysis on the threat of new entrants provided one possible explanation for this, namely that economies of scale is essential in such a capital-intensive industry as the oil & gas.

Another possible explanation is that the cyclical nature of the industry necessitates market participants to be large and diversified in their exposure to market risk – especially in periods of low crude oil or natural gas prices. Considering that the industry includes numerous upstream, midstream and downstream activities, large companies are better able to sustain unfavorable changes in economic conditions because of the diversification of their business lines. Through their diversification across the value chain and through their size, it is not surprising that the so called super majors in the data sample, ExxonMobil (Aaa), Chevron (Aa1), and ConocoPhillips (A1) are perceived to be highly creditworthy by Moody's.

The common denominator of both explanations boils down to size. Since all size variables are top ranked in the univariate analysis, it seems that Moody's emphasizes this aspect considerably when determining the creditworthiness of an oil & gas issuer.

In terms of leverage, the financial ratio analysis clarified that highly leveraged firms have a smaller cushion to unanticipated events. In the oil & gas industry, financial flexibility is central to carry out large investments in upstream and downstream projects, and these activities also necessitate an ongoing funding of extensive capital commitments. Bearing in mind the uncertainty surrounding the industry, it can be argued that its capital-intensive features explain why leverage metrics are significant in predicting credit ratings assigned to oil & gas firms. The fact that four leverage ratios are top ranked after size supports this claim, and suggests that leverage is a vital aspect to consider when determining the creditworthiness in this specific industry.

Capital intensity also explains why the only significant variable not related to size, profitability, or leverage is "EBITDA-CapEx to cash interest paid". It is the only interest coverage ratio that is significant. As seen in its contexture, the ratio is closely related to size and the capital-intensive nature of the industry. Therefore, it is inappropriate to argue for the need of interest coverage ratios in general.

There are two reasons why profitability appears to be a key measure when determining the creditworthiness of an oil & gas firm.

The size factor trickles down on profitability. Porter's Five Forces analysis revealed that the power of buyers is high and that firms have a limited ability to pass costs on to customers. Because of this price-taking feature, cost advantage in terms of economies of scale is a key success factor to gain competitive advantage. The high degree of rivalry supports this claim. Due to the commodity-based nature of the industry, competitive advantage is primarily achieved through operational efficiency. With this in mind, size and profitability appear to be interrelated in the oil & gas industry; the large scale of operations in e.g. oil exploration and production allows market participants to exploit supply-side economies of scale, which in turn reduces costs and enhances profitability.

The significance of profitability can also be explained by the uncertainty surrounding the oil & gas industry. Periods of low commodity prices increase the risk of falling into financial distress. At the end of the day, the future existence of an issuer revolves around the ability to generate profits to service debt. The highly cyclical nature of the industry provides an explanation to why profitability is another key measure to separate 'creampuffs' from 'lemons'.

7.2.2. Consumer Products

Based on the ANOVA results in Table 4 in Appendix, in descending order and on a standalone basis, the following 28 financial variables have a significant predictive power for estimating credit ratings in the consumers products industry.

Table 7.2.2.a *Univariate results in the Consumer Products industry*

	Financial variable	Ratio Group	F-test	1-pvalue
1	Return on Assets	Profitability	17,334	1,000000
2	Net Debt to EBITDA	Leverage	16,465	1,000000
3	Pretax Margin	Profitability	13,999	1,000000
4	Income before XO Margin	Profitability	13,631	1,000000
5	CFO to Total Liabilities	Cash Flow	13,271	0,999999
6	Profit Margin	Profitability	12,719	0,999999
7	Net Income to Common Margin	Profitability	12,643	0,999999
8	Return on Capital	Profitability	12,471	0,999999
9	Total Debt to EBIT	Leverage	11,540	0,999997
10	Net Debt to EBIT	Leverage	10,671	0,999993
11	Long Term Debt to Total Assets	Leverage	9,506	0,999978
12	Current Ratio	Liquidity	6,114	0,999102
13	EBITDA	Size	5,815	0,998734
14	Operating Margin	Profitability	5,644	0,998460
15	Long-Term Debt to Capital	Leverage	5,629	0,998432
16	EBIT	Size	5,365	0,997869
17	EBITDA Margin	Profitability	5,276	0,997633
18	EBITDA-CapEx	Size	5,255	0,997575
19	Total Debt to Total Assets	Leverage	5,119	0,997158
20	Altman's Z-Score	Altman	4,904	0,996053
21	Incremental Operating Margin	Profitability	4,006	0,989210
22	Return on Equity	Profitability	3,986	0,988827
23	Total Equity	Size	3,797	0,986312
24	Total Assets	Size	3,653	0,983719
25	Total Debt	Size	3,107	0,968474
26	Total Debt to Capital	Leverage	3,049	0,966167
27	Gross Margin	Profitability	2,971	0,962710
28	Net Debt to Capital	Leverage	2,947	0,961696

In contrast to the oil & gas industry, the variables that on a standalone basis are the best ones at predicting credit ratings belong to a more diverse group of ratio categories. Although six of the top ten ratios in the univariate list measure profitability, there is not a clear sequential trend among the ratio categories as in the oil and gas industry.

Profitability, size and leverage account for 89% of all the significant variables. In the oil & gas industry, the proportion is 95%. The remaining 11% (3) variables belong to two other ratio categories. In the oil & gas industry, the proportion is 5% (1) and the variable is closely linked to size and the capital-intensive characteristics of the industry.

The significant variables in the consumer products industry are as such slightly more dispersed. The disparity follows the same pattern as the majority of the previous studies. Perhaps, disparity is preferable because it captures a wider range of aspects to account for when assessing the creditworthiness of a firm.

What makes it interesting when comparing the univariate lists is that there is a clear-cut sequential order of the variables in oil & gas, while the variables are more distributed in the consumer products industry. This raises the question whether the characteristics of the oil & gas industry emphasize aspects related to size, leverage, and profitability to such a large extent, that other categories of financial variables become irrelevant. The fact that there are 25% more significant variables in the consumer products sample (28) than in the oil and gas (21) supports this hypothesis.

All but one profitability variable is significant in the consumer products industry. In the oil & gas industry, the figure is 7 of 12. The significance can be explained in light of Porter's Five Forces. The power of buyers is weak since the market contains many small-size buyers: fragmentation decreases their ability to influence the price of consumer products. Competitive advantage is primarily achieved trough differentiation, and market participants exploit brand recognition and customer loyalty to accomplish this.

Hence, the univariate step confirms that profitability is significant in both industries. The Five Forces framework suggests that the difference is that it is achieved through cost advantage in the oil & gas industry and by differentiation in the consumer products industry. In the next step, ratio analysis is conducted to examine this difference.

The univariate analysis demonstrates that all size variables are significant in both industries. However, all are top ranked in oil and gas, which is certainly not the case for consumer products. Table 7.2.2.b summarizes and compares the two industries in light of all the variables related to size. Expressed in millions of dollars, almost all of the variables, including EBITDA, are larger for oil & gas than for consumer products. There is one interesting exception, namely the variable "EBITDA-capital expenditures", which is much larger for consumer products firms.

It is argued that this explains the absence of size variables in the top of the univariate list. The characteristics of the industry, with smaller capital requirements and benefits of economies of scale, do not necessitate the need of being big in order to be considered creditworthy. In addition, consumer products are goods that are purchased by households for daily purposes. As measured by industry beta, the market uncertainty is lower than in the oil and gas industry. There is a smaller need for integration across the value chain – primarily reflected in the size of a firm – to decrease market risk.

Table 7.2.2.b –*Average size variables in millions of USD*

	Oil & Gas		**Consumer Products**		**Differences (OG-CP)**	
	IG	SG	IG	SG	IG	SG
Total Equity	213	21	130	18	83	3
Total Debt	54	11	55	13	-1	-2
Total Assets	266	33	185	30	81	3
EBITDA	3768	356	2950	324	818	32
EBIT	2621	174	2448	252	173	-78
EBITDA-CapEx	1549	-235	2346	255	-797	-490

7.3. Multicollinearity & univariate analysis of selected variables

7.3.1. Oil & Gas

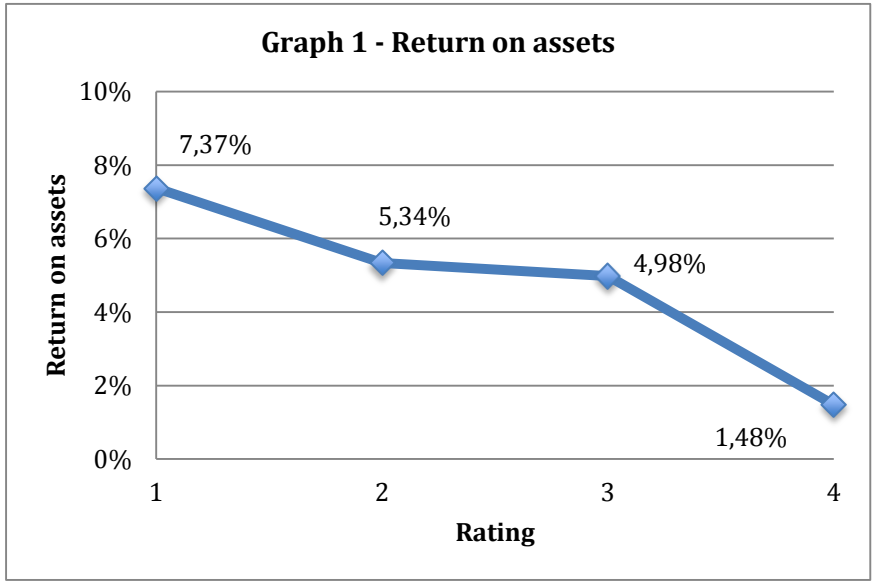
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	22
ROA	1																				
GM	0,06	1																			
OM	0,43	0,56	1																		
PtM	0,58	0,36	0,72	1																	
IXOM	0,58	0,31	0,66	0,97	1																
PM	0,60	0,31	0,66	0,95	0,98	1															
NICM	0,60	0,29	0,69	0,95	0,97	0,99	1														
LTDC	-0,32	-0,08	-0,27	-0,41	-0,37	-0,36	-0,39	1													
LTDTA	-0,38	-0,03	-0,19	-0,36	-0,31	-0,31	-0,34	0,92	1												
TDC	-0,32	-0,08	-0,28	-0,39	-0,36	-0,34	-0,37	0,99	0,91	1											
TDTA	-0,39	-0,02	-0,20	-0,35	-0,30	-0,29	-0,33	0,94	0,97	0,95	1										
TDEBITDA	-0,35	-0,19	-0,37	-0,26	-0,20	-0,20	-0,27	0,39	0,41	0,39	0,42	1									
NDEBITDA	-0,32	-0,19	-0,32	-0,23	-0,16	-0,17	-0,23	0,46	0,47	0,47	0,49	0,91	1								
EBITDA-CapEX to CIP	0,12	-0,18	-0,07	-0,04	0,03	0,03	0,02	0,17	0,13	0,18	0,14	0,03	0,24	1							
NDC	-0,37	-0,03	-0,20	-0,34	-0,30	-0,29	-0,32	0,93	0,89	0,94	0,93	0,41	0,52	0,20	1						
EBITDA	0,22	-0,06	0,05	0,08	0,04	0,04	0,05	-0,31	-0,33	-0,30	-0,32	-0,22	-0,20	0,16	-0,30	1					
EBITDACapEx	0,24	-0,17	0,01	0,05	0,03	0,02	0,03	-0,27	-0,27	-0,25	-0,27	-0,16	-0,15	0,16	-0,28	0,87	1				
EBIT	0,25	-0,08	0,06	0,08	0,04	0,04	0,06	-0,31	-0,33	-0,30	-0,33	-0,22	-0,20	0,16	-0,31	0,99	0,91	1			
TD	0,04	-0,09	0,04	0,02	0,00	-0,01	0,00	-0,12	-0,13	-0,09	-0,10	-0,07	-0,06	0,14	-0,06	0,57	0,32	0,53	1		
TA	0,14	-0,11	0,00	0,04	0,01	0,00	0,02	-0,31	-0,33	-0,29	-0,32	-0,19	-0,17	0,16	-0,27	0,91	0,72	0,87	0,81	1	
TE	0,16	-0,11	-0,01	0,05	0,01	0,00	0,02	-0,33	-0,36	-0,32	-0,35	-0,21	-0,19	0,16	-0,30	0,93	0,77	0,90	0,72	0,99	1

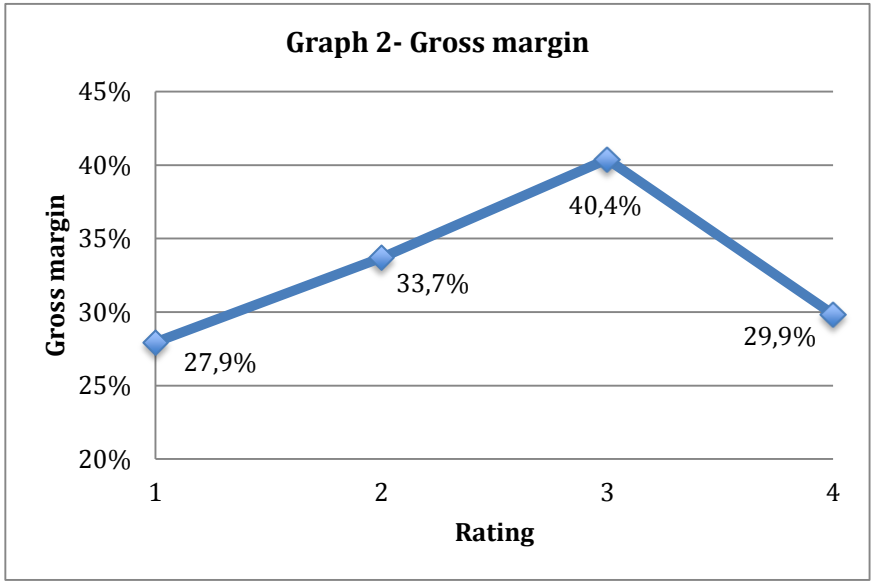
The correlation between the selected variables in the oil & gas industry is presented above. The matrix illustrates clusters of red-colored variables with similar characteristics that are highly positively correlated ($r>0,70; p<0.05$). This is an expected outcome and it is a sign of a healthy data sample.

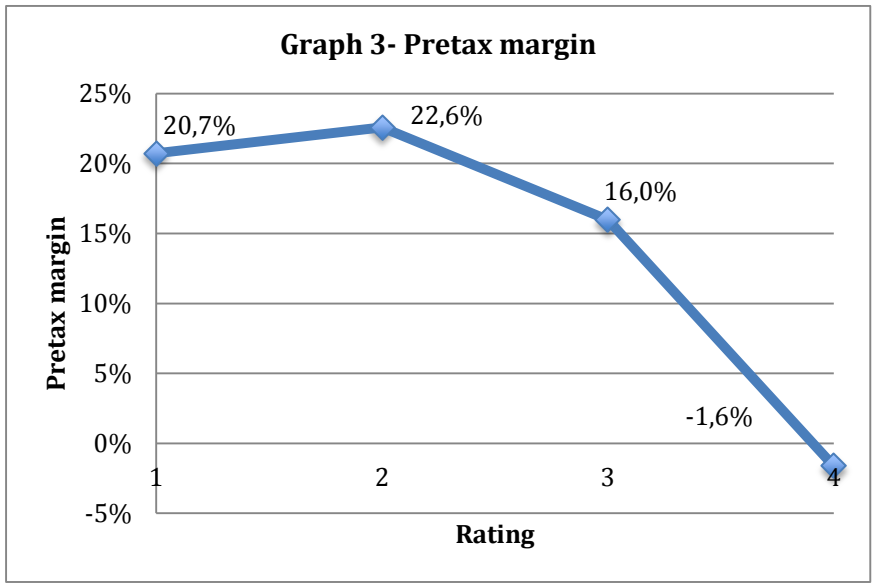
Pretax margin (highest on the univariate list among profitability ratios) is highly correlated with all variables related to profitability except for return on assets and gross margin. Return on assets and gross margin are not highly correlated with any other variables. Thus, pretax margin, return on assets and gross margin are the three profitability ratios that proceed to the next step.

By the same procedure, long-term debt to total assets and total debt to EBITDA (leverage), EBITDA-CapEx to cash interest paid (interest coverage), and total equity (size) proceeds to the next step. The univariate relationship between credit ratings and these variables is depicted on the next pages.

Profitability





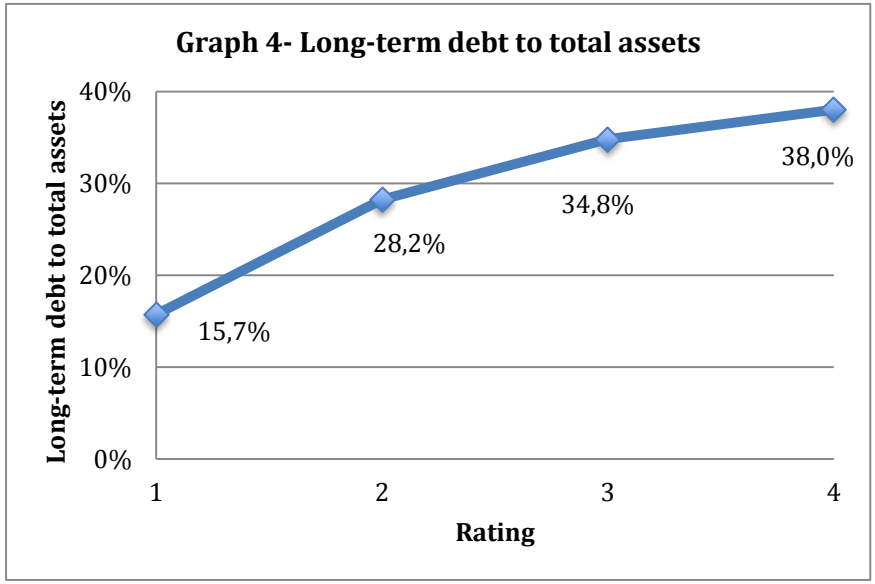


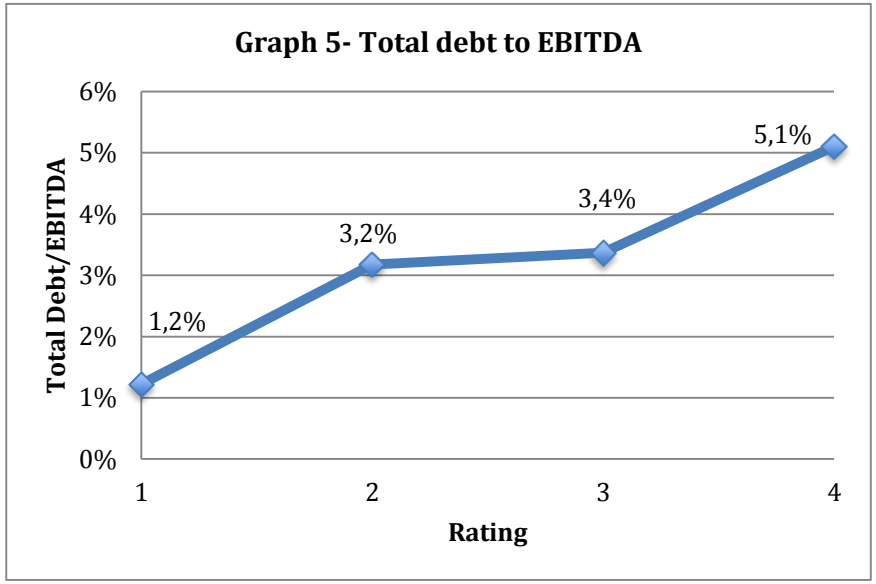
Graphs 1-3 illustrate the univariate relationships between three profitability measures (return on assets, pretax margin, and gross margin) and credit ratings. Return on assets, which measures a firm's ability to earn profits before leverage, appears as expected: the ratio decreases as the credit rating deteriorates. The pretax margin, which measures the operating efficiency of a firm, follows a similar pattern: although the margin is slightly higher for firms rated Baa than for firms in the highest category, it decreases substantially along the following non-investment grade credit ratings.

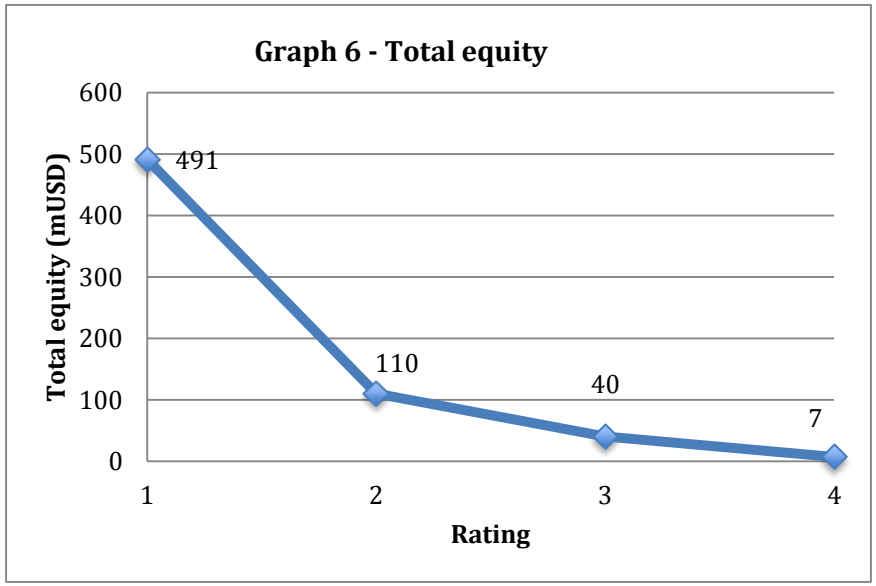
In contrast to these profitability measures, the relationship between gross margin and credit ratings contradicts the expected relationship: the gross margin decrease as the credit rating increases and firms in the fourth category exhibit a higher margin than firms in the first. Although the figures do not lie, that is the actual relationship based on the data sample; it is nevertheless impossible to justify the inclusion of a financial variable that contradicts financial theory. For that reason, gross margin is excluded from the prospective list of potential variables in the final credit model.

This discovery reveals an interesting detail regarding the ability to control costs. The gross margin shows that firms with a lower credit rating have higher revenues in proportion to the cost of goods sold. The pretax margin is on the other hand higher among more creditworthy firms. This indicates that the cost controlling ability, central in the oil & gas industry, is better among higher rated firms because the profits 'trickle down' unfavorably for lower rated firms. This will be elaborated upon in more detail in the next section by comparing the cost controlling ability in the two industries.

Leverage and Size







Graph 4 and 5 illustrate the relationship between two leverage ratios (long-term debt to total assets and total debt to EBITDA) and credit ratings.

Firms with a higher proportion of long-term debt in relation to total asset are considered to be riskier since they have more liabilities and less equity. Graph 4 illustrates a theoretically sound relationship as the proportion of long-term debt to total assets decreases as the credit rating increases. In other words, the higher the credit rating, the smaller amount of an issuer's assets are financed with loans and financial obligations lasting more than one year. The graph indicates that investment grade firms have a greater spare debt capacity than non-investment grade firms.

Section 2.5 clarified that Moody's rating methodology is focused on the fundamental factors that impact an issuer's ability to meet debt payments. 'Major economic downturns' was given as an example when ascertaining the importance of having a long-term focus when rating firms. Bearing in mind the uncertainty surrounding the oil & gas industry, the ability to make room for more debt without comprising the ability to service it is fundamental to ensure a confident future. A frequently applied ratio that evaluates this ability is debt to EBITDA.

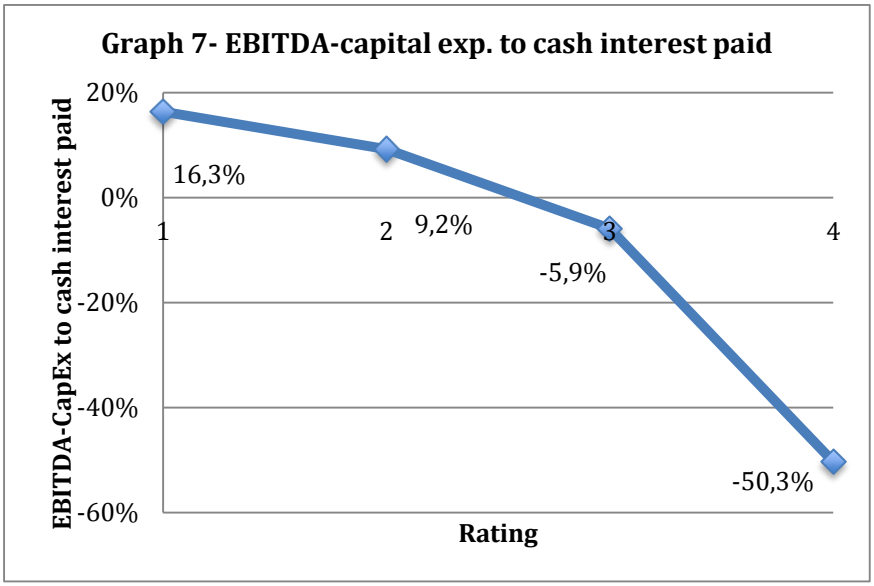
A high proportion of debt to EBITDA can cause a situation wherein firms are unable to service debt repayments appropriately. A low ratio is thus preferable for both creditors and issuers. For the latter, it makes room for more debt when necessary. For the former, it is a signal of creditworthiness as the conditions to service debt are favorable. Graph 5 illustrates this: the credit ratings deteriorate as the proportion of debt to EBITDA increases.

Graph 6 illustrates the relationship between total equity and credit ratings. The figure highlights that credit ratings increase with total equity, and that firms in the highest rating category have a much larger amount of total equity than any of the other rating categories. Table 7.3.1 examines this issue further and demonstrates that the higher the rating, the bigger and less leveraged are the issuers.

Table 7.3.1.a – *Capital structure divided per rating category in millions of USD*

	1	2	3	4
Total Equity	491	110	40	7
Total Debt	80	44	21	4
Total Assets	572	154	61	11
Debt to Assets	14%	28%	35%	36%

Interest Coverage



Graph 7 illustrates the only ratio that does not measure size, profitability, or leverage. Since none of the other ratios belonging to the 'interest coverage category' are significant, it is reasonable to assume that the significance of this particular ratio has to do with its relation to the capital-intensity of the industry. This manifests itself clearly when analyzing the relationship between the ratio and credit ratings. It follows a theoretically sound, yet extreme pattern. Investment grade companies display a positive figure, while speculative grade issuers display a negative figure.

As demonstrated in Table 7.3.1.b, the lower the rating, the higher is the amount of capital expenditures in relation to EBITDA. Among speculative grade issuers, the capital expenditures even exceed EBITDA. This might explain why lower-rated firms are also more indebted.

Table 7.3.1.b – *EBITDA less capital expenditures*

	1	2	3	4
EBITDA-CapEx	4271	617	-384	-134

7.3.2. Consumer Goods

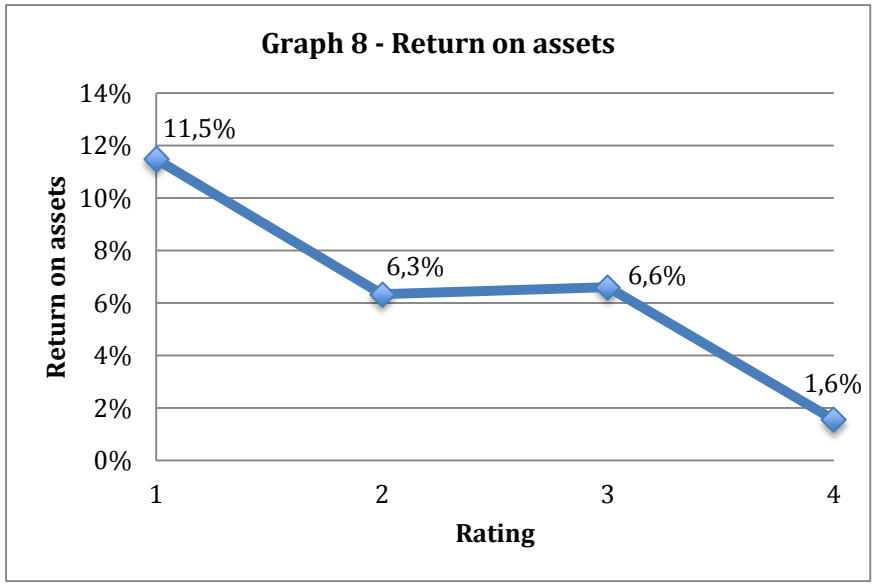
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
ROE	1																											
ROA	0,71	1																										
ROC	0,71	0,79	1																									
GM	0,24	0,38	0,39	1																								
EBITDAM	0,40	0,49	0,47	0,53	1																							
OM	0,41	0,54	0,51	0,54	0,99	1																						
IOM	0,32	0,29	0,18	-0,03	0,08	0,11	1																					
PtM	0,49	0,76	0,59	0,45	0,82	0,85	0,21	1																				
IXOM	0,46	0,76	0,56	0,40	0,77	0,78	0,25	0,98	1																			
PM	0,45	0,75	0,54	0,40	0,75	0,76	0,24	0,94	0,97	1																		
NICM	0,44	0,75	0,54	0,40	0,75	0,76	0,24	0,94	0,97	1,00	1																	
CR	-0,30	-0,09	-0,22	-0,17	-0,31	-0,27	-0,14	-0,19	-0,17	-0,13	-0,13	1																
LTDC	0,29	-0,09	0,07	0,05	0,06	0,03	0,06	-0,17	-0,10	-0,11	-0,11	-0,16	1															
LTDTA	0,15	-0,18	-0,07	-0,01	0,07	0,03	0,00	-0,18	-0,13	-0,14	-0,14	-0,07	0,93	1														
TDC	0,39	-0,02	0,15	0,09	0,12	0,08	0,11	-0,10	-0,04	-0,05	-0,05	-0,27	0,98	0,89	1													
TDTA	0,25	-0,10	0,02	0,04	0,14	0,10	0,06	-0,11	-0,06	-0,07	-0,07	-0,20	0,91	0,97	0,93	1												
CFOTL	0,27	0,60	0,37	0,32	0,22	0,25	0,12	0,42	0,36	0,35	0,35	0,06	-0,54	-0,59	-0,52	-0,57	1											
Z	0,22	0,53	0,21	0,21	0,10	0,14	0,16	0,27	0,22	0,23	0,22	0,32	-0,45	-0,36	-0,44	-0,36	0,78	1										
NDEBITDA	-0,34	-0,57	-0,39	-0,23	-0,18	-0,23	-0,19	-0,42	-0,39	-0,37	-0,37	0,00	0,51	0,69	0,46	0,65	-0,69	-0,42	1									
TDEBIT	-0,40	-0,60	-0,48	-0,24	-0,33	-0,36	-0,30	-0,48	-0,46	-0,44	-0,44	0,05	0,34	0,45	0,29	0,40	-0,56	-0,38	0,85	1								
NDEBIT	-0,38	-0,56	-0,43	-0,22	-0,28	-0,32	-0,30	-0,44	-0,43	-0,42	-0,42	0,01	0,35	0,48	0,30	0,43	-0,54	-0,35	0,89	0,99	1							
NDC	0,26	-0,07	0,05	0,06	0,11	0,06	0,07	-0,12	-0,06	-0,07	-0,07	-0,32	0,89	0,90	0,92	0,94	-0,55	-0,42	0,61	0,36	0,41	1						
EBITDA	0,18	0,29	0,32	0,20	0,49	0,49	0,03	0,51	0,50	0,44	0,43	-0,40	-0,12	-0,15	-0,07	-0,09	0,12	-0,06	-0,18	-0,19	-0,17	-0,05	1					
EBITDACapEx	0,19	0,29	0,32	0,20	0,51	0,51	0,04	0,53	0,51	0,45	0,45	-0,38	-0,12	-0,14	-0,07	-0,09	0,12	-0,06	-0,18	-0,20	-0,17	-0,05	0,99	1				
EBIT	0,18	0,30	0,32	0,20	0,50	0,50	0,04	0,52	0,51	0,44	0,44	-0,38	-0,12	-0,15	-0,07	-0,10	0,13	-0,05	-0,18	-0,20	-0,17	-0,05	1,00	1,00	1			
TD	0,11	0,13	0,16	0,15	0,41	0,38	0,06	0,39	0,42	0,37	0,37	-0,41	-0,02	-0,02	0,02	0,03	-0,05	-0,16	-0,02	-0,08	-0,06	0,05	0,89	0,86	0,86	1		
TA	0,09	0,15	0,17	0,13	0,39	0,38	0,04	0,40	0,42	0,38	0,38	-0,39	-0,11	-0,13	-0,07	-0,09	0,01	-0,13	-0,09	-0,12	-0,11	-0,05	0,93	0,91	0,91	0,97	1	
TE	0,07	0,16	0,17	0,12	0,38	0,37	0,03	0,40	0,41	0,38	0,38	-0,37	-0,15	-0,17	-0,11	-0,14	0,04	-0,11	-0,12	-0,14	-0,12	-0,09	0,93	0,91	0,92	0,94	0,99	1

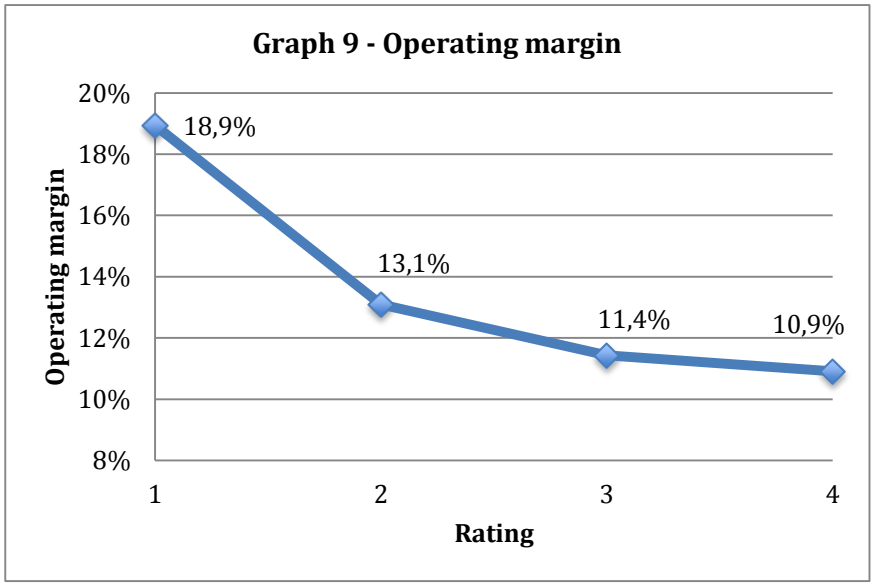
The correlation between the selected variables in the consumer goods industry is presented above. The matrix illustrates clusters of red-colored variables with similar characteristics that are highly positively correlated ($r>0,70;p<0,05$). This is an expected outcome and it is a sign of a healthy data sample.

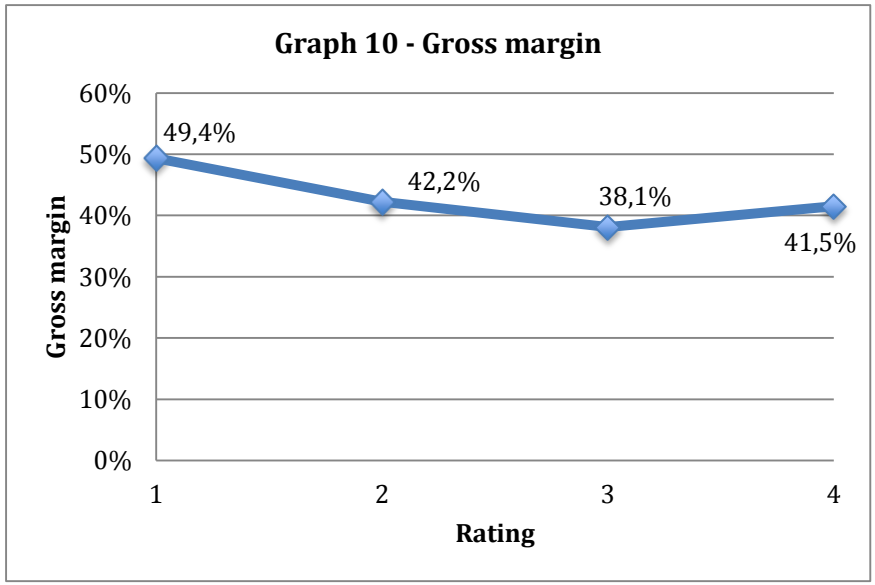
Return on assets (1st on the univariate list) is highly correlated with all variables related to profitability except for operating margin (14th), EBITDA margin (17th) and gross margin (27th). Operating margin is in turn highly correlated with EBITDA margin. Gross margin is not highly correlated with any other variable. Thus, return on assets, operating margin and gross margin are the three profitability ratios that proceed to the next step. By the same procedure, net debt to EBITDA and long-term debt to total assets (leverage), EBITDA (size), CFO to total liabilities and current ratio (liquidity) are not highly correlated with other variables and proceed to the next step.

In the latter case, one might expect that the only two liquidity ratios on the univariate list would follow a similar categorical pattern and be highly correlated with each other. However, despite being grouped in the same category, the ratios measure diverse aspects related to liquidity as explained in section 5.4. The relationship between credit ratings and the proceeding variables is depicted on the next pages.

Profitability







Graph 8-10 illustrate the univariate relationships between three profitability measures (return on assets, operating margin, and gross margin) and credit ratings. Despite a slight increase in return on assets between the 2nd and 3rd category, and in gross margin between the 3rd and 4th, all three ratios follow an expected pattern where the return and margins decrease as the credit quality deteriorates.

The gross margin highlights two important aspects in respect to the purpose of this thesis. Firstly, it is argued that the contradictory graphical plot of the gross margin in the oil & gas industry proves that there is a need for industry-specific credit rating models: the difference between the two industries indicates that it is unreasonable to apply a 'broad-brush approach' when creating models that replicate credit ratings.

Secondly, the graphical plot of the gross margin indicate that higher rated firms provide products that customers are paying a price premium for: it is argued that these firms are able to differentiate their products so that the price exceeds the cost of the good sold to a larger extent than lower rated firms. This argument is applicable in comparison to oil & gas as well. Table 7.3.2.a shows that except for the 3rd rating category, the gross margin is consistently higher in the consumer products industry.

Table 7.3.2.a – Comparison of Gross Margin across all rating categories

	1	2	3	4
Consumer P.	49%	42%	38%	42%
Oil & Gas	28%	34%	40%	30%

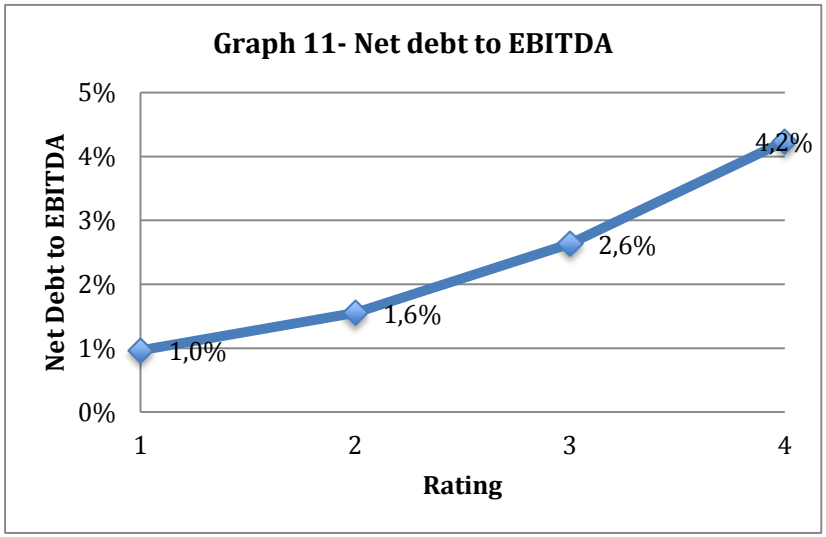
By comparing how the profits 'trickle down' in the two industries, it is argued that the cost controlling ability is better in the oil & gas industry. This reaffirms both the Five Forces analysis , and that the interpretation of financial variables must differ depending on the industry since the same financial ratio can have a different meaning for firms operating in different industries.

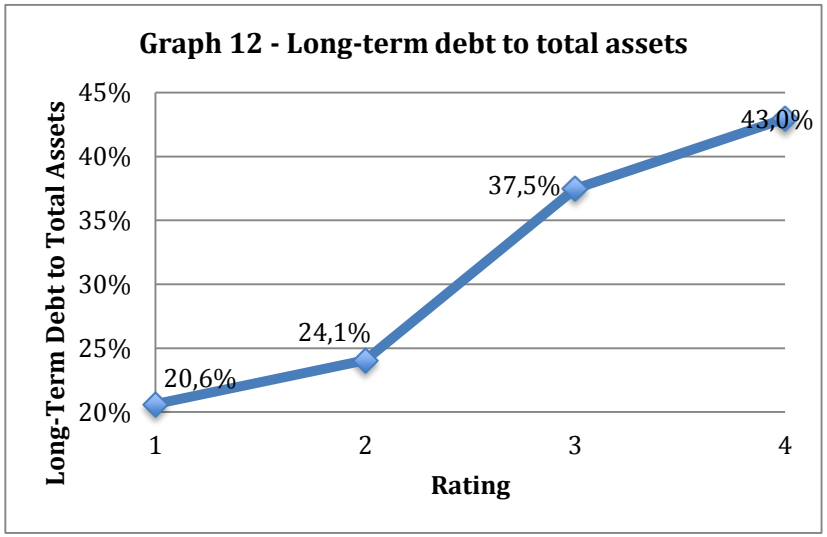
Table 7.3.2.b – *Comparison of cost controlling ability*

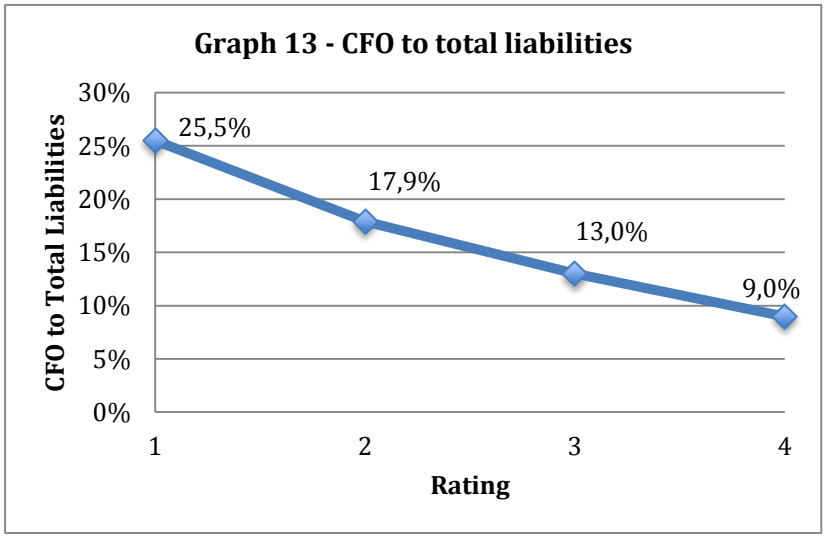
	Oil & Gas	Δ%	Consumer P.	Δ%
Gross margin	33,47		43,47	
EBITDA margin	37,81	13%	17,56	-60%
EBIT margin	17,68	-53%	14,16	-19%
EBT margin	11,49	-35%	10,68	-25%
Profit margin	8,45	-26%	7,55	-29%

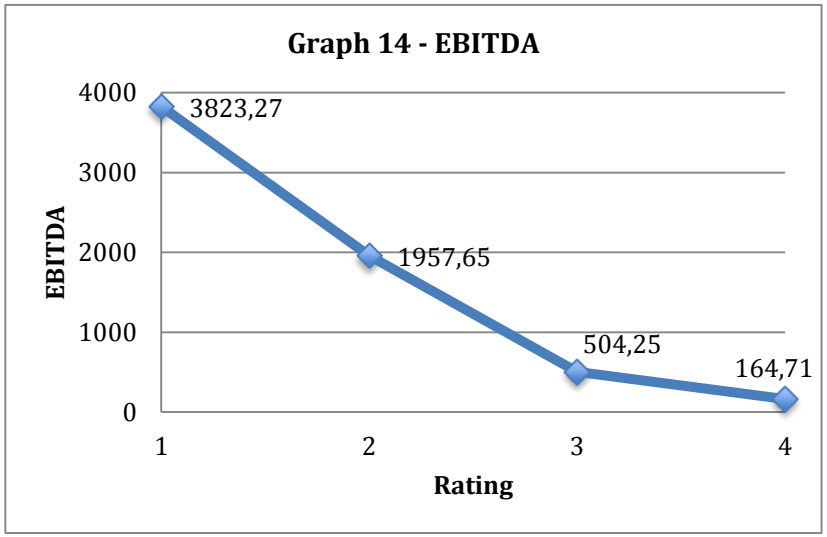
Amongst other, the gap between gross margin and EBITDA margin includes staff costs, distribution and administrative costs and other operating income. The table shows that oil & gas companies are much better at controlling these costs than firms in the consumer products industry. The difference between EBITDA margin and EBIT margin shows that depreciation and amortization accounts for a larger portion of the revenues in the oil & gas industry, which reaffirms its capital-intensive nature.

Leverage, Liquidity and Size







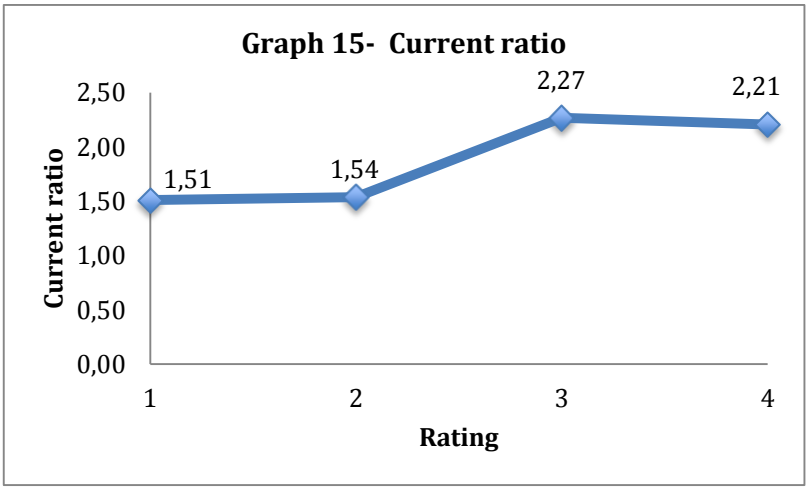


Graph 11 and 12 illustrate the univariate relationships between two leverage measures (net debt to EBITDA and long-term debt to total assets) and credit ratings. Long-term debt to total assets increases as the credit rating decreases, which means that more debt constitutes total assets as the credit rating decreases. Net debt to EBTIDA also increases as the credit rating decreases, which means that less and less EBITDA is available to cover net debt as the credit rating deteriorates. Both industries incorporate a debt to EBITDA measure. This proves that the fundamental factors that impact an issuer's ability to meet debt payments are vital across all industries.

Graph 13 displays the proportion of cash flow from operation to total liabilities in relation to credit ratings. The ratio indicates the ability to cover total debt payments with cash generated from operating activities. The lower the ratio, the lower the cash and the riskier the financial position of a firm. The graph illustrates an expected plot, whereby high-rated firms are more capable to cover their total liabilities by CFO than lower-rated firms.

Finally, EBITDA in Graph 14 also follows a theoretically sound line. Similar to the oil & gas industry where the size factor was mirrored through total equity, companies in the highest rating group have a significantly larger EBITDA than the other rating classes. In this case, EBITDA in rating class 1 is almost twice the EBITDA in rating class 2.

Liquidity



Graph 15 illustrates the current ratio. In line with the findings of Resti (2002), a liquidity puzzle is observed where the current ratio is higher among speculative grade firms than investment grade firms. As stated in the financial ratio analysis, a higher current ratio is in general desirable. Yet, Graph 15 shows that the current ratio is much higher among speculative grade firms than for investment grade firms. At first, this appears to contradict financial theory.

However, the explanation to this can be deducted from the 'Cash Conversion Cycle'. In short, the cycle reflects management effectiveness by calculating how many days it takes to convert products into cash through sales[6]. Retrieved from Bloomberg, table 7.3.2.c shows that the cycle is 17 days shorter among investment grade firms than for speculative grade firms. Hence, although the current ratio is lower, investment grade firms are better able to quickly convert its products into cash through sales.

Table 7.3.2.c – *Cash Conversion Cycle*

	1	**2**	**3**	**4**	**IG**	**SG**
Cash Conversion Cycle	75	83	104	90	79	96

In light of the CCC, it seems that lower rated firms achieve a higher ratio due to a buildup of accounts receivable and a longer collection period. A lower current ratio is generally regarded as unfavorable, but in this case, it seems to be the result of efficient use of working capital.

[6] The cash conversion cycle is calculated as days inventory outstanding + days sales outstanding – days payable outstanding.

7.4. Multivariate analysis

7.4.1. Oil & Gas

Model Summary

R	R square	Adjusted R square	Std. Error of the estimate	Durbin-Watson statistic
0,66	0,435	0,407	0,784	0,811

Coefficients

Model	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
(constant)	2,711	0,232		11,688	0
TotalEquity	-0,002	0	-0,448	-5,893	0
TotalDebtTotalAssets	0,01	0,006	0,155	1,715	0,089
PretaxMargin	-0,008	0,003	-0,236	-2,822	0,006
ROA	0,012	0,014	0,075	0,844	0,4
TotalDebtT12MEBITDA	0,021	0,022	0,073	0,921	0,359
EBITDACapExCashInterestPaid	-0,003	0,001	-0,256	-3,518	0,001

Anova

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	56,912	6	9,485	15,421	,000[b]
Residual	73,813	120	0,615		
Total	130,724	126			

The proposed model is well suited to the data sample (f6, 120) = 15,421 p<0,05. Based on the results of the regression, it is concluded that Total Equity (beta=-0,45, p <0,05), Pretax Margin (beta=-0,24, p <0,05), and EBITDA-Capex to Cash Interest Paid (beta=-0,26, p <0,05) is the optimal combination of independent variables. This means that Total Equity, Pretax Margin and EBITDA-Capex to Cash Interest Paid are the variables that are included in the final model. The final replicating credit rating model can be expressed in the form of the following regression:

Y = 2,71 + ([-0,002] x Total Equity) + ([-0,008] x Pretax Margin) + ([-0,003] x EBITDA-CapEx to Cash Interest Paid).

The lower the y-value, the better the rating. The negative coefficients mean that the higher the total equity, the pretax margin, and the proportion of EBITDA less capital expenditures to cash interest paid, the lower is the y-value and the higher is the creditworthiness of any given company operating in the oil & gas industry.

The tested model explains 44% of the dependent variable.

7.4.2. Consumer Goods

Model Summary

R	R square	Adjusted R square	Std. Error of the estimate	Durbin-Watson statistic
0,833	0,694	0,658	0,658	1,2

Coefficients

Model	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
(Constant)	1,464	0,425		3,442	0,001
ROA	-0,077	0,021	-0,383	-3,594	0,001
NetDebtEBIT	0,008	0,023	0,031	0,335	0,738
CFOTotalLiabilities	-0,014	0,012	-0,136	-1,222	0,226
LongTermDebtTotalAssets	0,024	0,006	0,368	3,734	0
CurrentRatio	0,512	0,105	0,363	4,883	0
EBITDA	-2,80E-05	0	-0,084	-1,01	0,316
OperatingMargin	-0,001	0,015	-0,009	-0,09	0,928
GrossMargin	0,001	0,007	0,008	0,099	0,922

Anova

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	66,69	8	8,336	19,255	0
Residual	29,44	68	0,433		
Total	96,13	76			

The proposed model is well suited to the data sample f(8,68)=19,225 p<0,05. Based on the results of the regression, it is concluded that return on assets (beta=-0,38, p <0,05) long-term debt to total assets (beta=0,37, p <0,05) and current ratio (beta=0,36, p <0,05) is the optimal combination of independent variables.

This means that return on assets, long-term debt to total assets, and current ratio are the variables that are included in the final model. The final replicating credit rating model can be expressed in the form of the following regression equation:

$$Y = 1{,}464 + ([-0{,}077] \times ROA) + (0{,}024 \times \text{Long-term debt to total assets}) + (0{,}512 \times \text{Current ratio})$$

The model suggests that the lower the amount of long-term debt to total assets and current ratio, and the higher the return on assets, the lower is the y-value and the higher is the creditworthiness of any given company operating in the consumer products industry. The observed liquidity puzzle is mirrored by the fact that the higher the current ratio, the lower is the creditworthiness of an issuer.

The tested model explains 70% of the dependent variable.

7.5. Model validation

Table 7.5.a – *Hit-mismatch for Oil & Gas*

	Predicted						
Obs.	1	2	3	4	Missing	Concordant	Discordant
1	5	7	1	0	1	39%	62%
2	2	29	5	0	3	81%	19%
3	0	15	18	0	5	55%	46%
4	1	11	33	0	11	0%	100%
						41%	**59%**

Table 7.5.b – *Hit-mismatch for Consumer Products*

	Predicted						
Obs.	1	2	3	4	Missing	Concordant	Discordant
1	4	19	2	0	0	16%	84%
2	0	15	7	0	0	68%	32%
3	0	2	13	0	0	87%	13%
4	0	1	6	9	0	56%	44%
						53%	**47%**

Table 7.5.c – *Hit-mismatch for Oil & Gas with 2 categories*

	Concordant	Discordant
Investment grade	87,8%	12,2%
Speculative grade	65,4%	34,6%
Overall	**74,0%**	**26,0%**

Table 7.5.d – *Hit-mismatch for Consumer Products with 2 categories*

	Concordant	Discordant
Investment grade	80,9%	19,1%
Speculative grade	90,3%	9,7%
Overall	**84,6%**	**15,4%**

The hit-mismatch matrices that include all rating categories prove that both models have a weak ability to accurately replicate ratings assigned by Moody's. The concordance rates in both models are far from acceptable for any practical usage of the models. However, the variables in the final rating models are statistically significant, and they differ between the models. For that reason one can point out the existence of industrial differences, and in the end argue for the need of industry-specific credit rating models.

The consumer products model performs much better than the oil & gas model. Accounting for all rating categories, it is able to correctly predict 53% of the rated firms (oil & gas 41%). The discordance is highest in the 1st category, where 84% of the sample is improperly placed in the 2nd category. The discordance rate in the oil & gas model is highest in the 4th category, where none of the issuers are correctly predicted. The concordance rate in both models is highest among firms on the threshold: both the oil & gas (81% and 55%) and the consumer products model (68% and 87%) are best at replicating ratings assigned to firms that are grouped in the 2nd and 3rd rating category.

The weak performance of the models implies that financial fundamentals are insufficient to replicate credit ratings assigned by Moody's, especially since the complete scale includes a broader range of ratings and notches. The industry analysis proposes that there are other non-financial but quantifiable variables that can be included to enhance the predictive power of the models. This might especially be the case for oil & gas: R^2 shows that the explanatory power of the model is only 44%, and the predictive ability of the model is inferior to consumer products despite the fact that the data sample was 88% larger.

The predictive power of the models increases significantly when the hit-mismatch matrices only include two rating categories, investment grade and speculative grade. The consumer products model correctly predicts 85% of the rated firms (oil & gas 74%). When used as an independent second opinion, especially the consumer products model can be used as a 'back of the envelope' tool to determine whether an unrated firm is a 'creampuff' or a 'lemon'.

The model validation shows that human judgment and qualitative analysis cannot be replaced when assessing the creditworthiness of an issuer. However, industry analysis indicates that accounting for industry-specific non-financial variables can enhance quantitative replicating credit rating models.

7.6. The complete model

7.6.1. Univariate analysis

	Financial variable	Ratio Group	F-test	1-pvalue
1	EBITDA	Size	25,484	1,000000
2	EBIT	Size	25,085	1,000000
3	Total Assets	Size	23,729	1,000000
4	Total Equity	Size	23,191	1,000000
5	EBITDA-CapEx	Size	21,093	0,999999
6	Return on Assets	Profitability	19,004	0,999998
7	Long-term Debt to Assets	Leverage	17,705	0,999998
8	Total Debt	Leverage	15,936	0,999991
9	Total Debt to Assets	Leverage	10,902	0,999990
10	Long-term Debt to Capital	Leverage	10,899	0,999990
11	Pretax Margin	Profitability	9,278	0,999969
12	Net Income to Common Margin	Profitability	9,162	0,999968
13	Net Debt to EBITDA	Leverage	9,168	0,999952
14	Income before XO Margin	Profitability	8,277	0,999941
15	Total debt to EBITDA	Leverage	8,268	0,999802
16	Altman's Z-Score	Other	8,045	0,999532
17	Profit Margin	Profitability	7,776	0,999406
18	Total Debt to EBIT	Leverage	6,856	0,999322
19	Net Debt to Capital	Leverage	6,193	0,998766
20	EBITDA-CapEx to Cash Interest Paid	Interest coverage	6,029	0,998727
21	Net Debt to EBIT	Leverage	5,915	0,997482
22	Total Debt to Capital	Leverage	5,456	0,987816
23	Operating Margin	Profitability	5,431	0,979588
24	Return on Equity	Profitability	4,919	0,977868
25	EBITDACapExInterestExpense	Interest coverage	3,727	0,955646
26	Return on Capital	Profitability	3,336	0,918196
27	Gross Margin	Profitability	3,269	0,860464
28	CFO to Current Liabilities	Liquidity	2,738	0,852285

7.6.2. Multicollinearity

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
EBITDA	1																											
EBIT	0,99	1																										
TA	0,91	0,88	1																									
TE	0,93	0,89	0,99	1																								
EBITDACapEx	0,90	0,94	0,77	0,79	1																							
ROA	0,25	0,27	0,15	0,15	0,29	1																						
LTDTA	-0,27	-0,27	-0,26	-0,30	-0,24	-0,33	1																					
TD	0,68	0,67	0,85	0,76	0,57	0,09	-0,08	1																				
TDTA	-0,25	-0,24	-0,24	-0,29	-0,20	-0,29	0,96	-0,03	1																			
LTDC	-0,22	-0,21	-0,21	-0,25	-0,18	-0,19	0,89	-0,06	0,91	1																		
PtM	0,12	0,12	0,08	0,08	0,10	0,55	-0,30	0,07	-0,28	-0,29	1																	
NICM	0,09	0,09	0,06	0,05	0,08	0,57	-0,28	0,05	-0,26	-0,27	0,95	1																
NDEBIT	-0,16	-0,17	-0,10	-0,11	-0,17	-0,39	0,32	-0,05	0,30	0,20	-0,20	-0,21	1															
IXOM	0,08	0,08	0,05	0,04	0,08	0,54	-0,26	0,05	-0,24	-0,26	0,97	0,97	-0,18	1														
TDEBITDA	-0,20	-0,20	-0,15	-0,17	-0,17	-0,37	0,38	-0,06	0,37	0,30	-0,23	-0,24	0,34	-0,17	1													
Z	0,05	0,09	-0,01	0,00	0,17	0,53	-0,49	-0,06	-0,45	-0,46	0,23	0,25	-0,36	0,23	-0,35	1												
PM	0,07	0,08	0,04	0,04	0,06	0,55	-0,26	0,04	-0,23	-0,25	0,95	0,99	-0,18	0,98	-0,17	0,22	1											
TDEBIT	-0,17	-0,18	-0,11	-0,12	-0,18	-0,40	0,29	-0,05	0,27	0,18	-0,21	-0,22	0,99	-0,19	0,33	-0,32	-0,19	1										
NDC	-0,19	-0,19	-0,17	-0,22	-0,17	-0,23	0,88	0,00	0,92	0,91	-0,25	-0,23	0,27	-0,21	0,33	-0,49	-0,21	0,22	1									
EBITDA-CapEx to CIP	0,11	0,11	0,10	0,10	0,13	0,18	0,02	0,07	0,04	0,05	-0,03	0,02	0,00	0,02	-0,02	-0,18	0,02	-0,06	0,05	1								
NDEBITDA	-0,20	-0,20	-0,15	-0,17	-0,17	-0,38	0,50	-0,05	0,49	0,40	-0,24	-0,24	0,41	-0,17	0,83	-0,44	-0,17	0,34	0,48	0,14	1							
TDC	-0,18	-0,17	-0,18	-0,22	-0,12	-0,14	0,85	-0,01	0,91	0,98	-0,27	-0,24	0,18	-0,23	0,27	-0,39	-0,23	0,15	0,92	0,07	0,37	1						
OM	0,11	0,11	0,06	0,05	0,07	0,39	-0,13	0,09	-0,13	-0,18	0,72	0,69	-0,25	0,66	-0,30	0,11	0,66	-0,27	-0,12	-0,08	-0,29	-0,17	1					
ROE	0,12	0,15	0,05	0,04	0,18	0,71	-0,04	0,05	0,00	0,15	0,24	0,27	-0,29	0,24	-0,23	0,35	0,24	-0,30	0,06	0,11	-0,23	0,21	0,16	1				
EBITDA-CapEx to IE	0,10	0,10	0,09	0,09	0,11	0,16	-0,08	0,06	-0,06	-0,04	0,03	0,05	-0,06	0,04	-0,04	0,08	0,04	-0,07	0,03	0,21	-0,04	-0,02	0,04	0,09	1			
ROC	0,15	0,18	0,06	0,07	0,21	0,69	-0,06	0,01	-0,02	0,11	0,07	0,10	-0,22	0,08	-0,10	0,24	0,10	-0,23	0,03	0,19	-0,15	0,15	0,01	0,82	0,10	1		
GM	0,01	0,02	-0,03	-0,05	0,00	0,19	-0,04	0,02	0,00	-0,01	0,33	0,28	-0,24	0,28	-0,20	0,16	0,29	-0,25	0,01	-0,07	-0,23	0,02	0,49	0,10	-0,05	0,00	1	
CFOAvgCurrentLiab	-0,08	-0,10	-0,12	-0,10	-0,16	0,06	0,15	-0,14	0,08	0,00	0,31	0,30	0,07	0,32	0,00	-0,17	0,35	0,05	0,03	-0,13	0,02	-0,06	0,36	0,02	-0,12	0,00	0,19	1

7.6.3. Multivariate analysis

Model summary

R	R-square	Adjusted R-square	Std. Error of the estimate
0,727	,528	,478	,770

Coefficients

Model	Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
(constant)	2,565	,337		7,618	,000
EBITDA	-2,254E-07	,000	-,001	-,008	,994
ROA	-,055	,025	-,273	-2,189	,030
LongTermDebtTotalAssets	,016	,006	,222	2,443	,016
TotalDebt	-,006	,002	-,333	-3,612	,000
PretaxMargin	,001	,005	,013	,134	,894
TotalDebtT12MEBITDA	,398	,142	1,059	2,814	,006
AltmansZScore	-,062	,046	-,116	-1,339	,183
TotalDebtEBIT	,005	,008	,044	,629	,530
EBITDACapExCashInterestPaid	-,002	,001	-,162	-2,345	,021
NetDebtEBITDA	-,389	,142	-1,060	-2,733	,007
EBITDACapExInterestExpense	-,001	,001	-,090	-1,436	,153
ROC	,000	,013	,003	,028	,978
GrossMargin	-,005	,005	-,076	-1,055	,294
CFOAvgCurrentLiab	,097	,114	,068	,852	,396

Anova

Model	Sum of squares	df	Mean Square	F	Sig.
Regression	86,797	14	6,200	10,467	,000[b]
Residual	77,594	131	,592		
Total	164,390	145			

The proposed model is well suited to the data sample f(14,131)=19,225 p<0,05. Based on the results of the regression, it is concluded that return on assets (beta=-0,055, p<0,05), long-term debt to total assets (beta=0,16, p<0,05), total debt (beta=-0,006, p<0,05), total debt to EBITDA (beta=0,398, p<0,05), EBITDA-CapEx to CIP (beta=-0,002, p<0,05), and net debt to EBITDA (beta=-0,389, p<0,05) is the optimal combination of independent variables.

The final replicating credit rating model can be expressed in the form of the following regression:

Y = 2,565 + ([-0,055] x Return on Assets) + ([0,16] x Long-term debt to Total Assets) + ([-0,006] x Total Debt) + ([0,398] x Total Debt to EBITDA) + ([-0,002] x EBITDA-CapEx to CIP) + ([-0,389] x Net Debt to EBITDA)

7.6.4. Model validation

Table 7.6.4.a – *Hit-mismatch for the complete model*

	Predicted					
Obs.	1	2	3	4	Concordant	Discordant
1	2	11	26	0	5%	95%
2	0	5	49	7	8%	92%
3	0	1	32	20	60%	40%
4	3	0	18	52	71%	29%
					40%	**60%**

Table 7.6.4.b – *Hit-mismatch for the complete model with 2 categories*

	Concordant	Discordant
Investment grade	18,0%	82,0%
Speculative grade	96,8%	3,2%
Overall	**61,9%**	**38,1%**

The correlation matrix reveals that the correlations among the variables in the complete model are weaker than in the industry-specific models. For that reason more variables are included in the final model. Nevertheless, the ability of the model to accurately predict credit ratings assigned to any given firm in the data sample is much weaker than the ability of the industry-specific models.

8. Conclusion

The purpose of this thesis was to evaluate whether there exists a need for industry-specific rating models that can replicate credit ratings assigned by Moody's. The following conclusions can be drawn with respect to the research questions put forth.

1. **To what extent can the industry-specific credit rating models predict the ratings assigned by Moody's?**

The oil & gas (consumer products) model correctly predicts 41% (53%) of the observed ratings. Accounting for two rating categories, the model is able to correctly predict 74% (85%) of the observed ratings. Measured by R^2, 44% (70%) of the credit ratings can be explained by the model.

2. **Does the predictive power increase when a replicating credit rating model is developed inside the confines of a specific industry?**

In the hit-mismatch matrices that account for all rating categories, the number of concordant pairs is higher among the industry-specific models than in the complete model. The number of concordant pairs in the hit-mismatch matrices that account for two categories is also higher among the industry-specific models.

The complete model is biased downwards and frequently predicts lower ratings. In the hit-mismatch matrix that accounts for two rating categories, the model correctly predicts 97% of all speculative grade firms, while it is only able to predict 18% of the investment grade issuers. On average, the complete model correctly predicts 62% of the firms in this hit-mismatch matrix. In comparison, the oil & gas model correctly predicts 88% of all investment grade firms, 66% of the speculative grade firms, and 74% on average. For consumer products, the percentages are 81%, 90%, and 85%. Hence, even though the complete model includes twice as many variables, its ability to accurately predict credit ratings is inferior to the industry-specific models.

Therefore, it is concluded that the predictive power increases when a replicating credit rating model is developed inside the confines of a specific industry.

3. **Which financial variables prove to be most significant in the replicating credit rating models, and do the variables differ between the three models?**

The first hint that the variables differ between the models was given in the univariate analysis. It showed that the most significant categories of financial variables are much more sequential in the oil & gas industry than in the consumer products industry.

The graphical analysis confirmed this by illustrating that certain variables, such as gross margin, differed substantially between the industries. The graphical analysis also showed that certain fundamental factors that impact the ability to meet debt payments, such as debt to EBITDA, were vital across both industries.

The final oil & gas model includes total equity (size), pretax margin (profitability), and EBITDA-CapEx to cash interest paid (interest coverage). The final consumer products model includes return on assets (profitability), long-term debt to total assets (leverage), and current ratio (liquidity). The complete model includes return on assets, long-term debt to total assets, total debt, total debt to EBITDA, EBITDA-CapEx to cash interest paid, and net debt to EBITDA.

The variables in the final rating models are statistically significant, and they differ between the models. For that reason one can point out the existence of industrial differences and argue for the need of industry-specific credit rating models.

4. **Are the financial variables that have proved to be significant in earlier studies also significant in the industry-specific models?**

All of the ratios in the final consumer products model have been included in previous studies; Return on assets was included in the models proposed by Kaplan & Urwitz (1979) and Ohlson (1980), Pinches & Mingo (1973) and Gray et al (2006) included long-term debt to total assets, while the current ratio was included by Amdouni & Soumaré (2013) and Resti (2002).

None of the variables in the final oil & gas model are included in the previous studies. This indicates that there are other, non-financial variables that must be taken into consideration in this industry. This might also explain why the explanatory power of the model and the hit-mismatch results are much lower than in the consumer products model. Above all, it emphasizes the inappropriateness of lumping all industries together when creating models that replicate ratings.

8.1. Concluding remarks and suggestions for future research

This thesis has lifted the lid to the black box that is rating methodology. The three models proposed are far from perfect, and their discordance make them far from applicable in assessing the creditworthiness of a firm. It seems that the present-day samples are too small in order to make industry-specific models. It is likely that the prediction rate improves as the number of rated issuers in both industries increases. To quote Ohlson (1980) "the predictive power of any model depends upon which information is available".

However, the common denominator of all credit models is the search for a better understanding, rather than the culmination of research. From this perspective, the conclusions drawn from this thesis bridge the research gaps identified. The thorough examination of the industrial differences has clarified whether, how, and why replicating rating models differ depending on the industry they are based on. The study has moreover highlighted certain aspects that firms in both industries can consider in order to gain a higher credit rating. As such, the thesis has answered the question whether there is a need for industry-specific credit rating models. There is.

As a suggestion for future research, and to enhance the oil & gas model, it is advised to include variables that are related to the underlying drivers of competitiveness and production capability, such as e.g. oil reserves or number of barrels produced per day. Regulatory licenses and whether the company is state owned or not can also be quantified and tested. Regarding the consumer products model, aspects such as reputation, customer loyalty and brand awareness can be quantified and tested to assess whether the predictive power increases. As the number of rated issuers increase, it might also be a good idea to be even narrower in the specificity of the models. By conducting e.g. a strategic group division, one could analyze which ratios prove to be significant, and assess whether the predictive power of the models is enhanced.

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Appendix

Table 1 – Consumer Products Issuers

Aa3	2007-06-12	Colgate-Palmolive Company	Ba2	2014-04-28	Levi Strauss & Co.
Aa3	1993-07-26	Coca-Cola Company (The)	Ba2	2013-11-14	Brunswick Corporation
Aa3	2001-10-19	Procter & Gamble Company (The)	Ba2	2010-02-17	TreeHouse Foods, Inc.
Aa3	2003-04-08	Gillette Company (The)	Ba2	2010-01-11	Scotts Miracle-Gro Company
A1	2000-07-11	Bestfoods	Ba2	2014-02-24	PVH Corp.
A1	2013-05-01	Unilever Capital Corporation	Ba2	2013-06-25	Keurig Green Mountain, Inc.
A1	2008-04-29	NIKE, Inc.	Ba3	2013-02-05	Revlon Consumer Products Corp
A1	2011-05-18	Alberto-Culver Company	Ba3	2014-05-14	Elizabeth Arden, Inc.
A1	2013-08-02	Hershey Company (The)	Ba3	2013-11-07	Wolverine World Wide Inc
A1	2011-09-20	Brown-Forman Corporation	Ba3	2014-05-15	B&G Foods, Inc.
A1	2013-06-25	PepsiCo, Inc.	Ba3	2013-06-19	H.J. Heinz Company
A2	2011-04-04	Hormel Foods Corporation	Ba3	2013-09-13	Jarden Corporation
A2	2007-03-21	Estee Lauder Companies Inc. (The)	B1	2014-02-12	Griffon Corporation
A2	2004-04-30	McCormick & Company	B1	2013-07-11	Post Holdings, Inc.
A2	2007-07-24	Kimberly-Clark Corporation	B1	2014-03-18	Bauer Performance Sports Ltd.
A2	2014-03-20	Anheuser-Busch InBev Inc	B1	2013-12-03	Prestige Brands, Inc.
A2	2008-03-06	Philip Morris International Inc.	B1	2012-06-13	Boulder Brands, Inc
A2	2008-08-06	Campbell Soup Company	B1	2012-11-05	Tempur-Pedic International Inc.
A3	2012-05-09	Diageo Investment Corporation	B1	2013-12-20	Perry Ellis International, Inc.
A3	2013-06-05	V.F. Corporation	B2	2014-02-19	Big Heart Pet Brands, Inc.
A3	2013-11-07	General Mills, Inc.	B2	2014-05-30	Central Garden & Pet Company
A3	2014-05-29	Ralph Lauren Corporation	B2	2014-03-21	Vector Group Ltd.
A3	2010-09-21	Coca-Cola Enterprises, Inc.	B2	2014-03-20	Easton-Bell Sports, Inc.
A3	2011-10-13	J.M. Smucker Company (The)	B2	2014-02-04	American Greetings Corporation
A3	2013-03-12	B.A.T Capital Corporation	B3	2014-01-30	Diamond Foods, Inc.
Baa1	2011-04-29	Mattel, Inc.	B3	2013-07-23	Quiksilver, Inc.
Baa1	2011-05-18	Dr Pepper Snapple Group, Inc.	B3	2013-11-19	Visant Corporation
Baa1	2014-05-07	Mondelez International, Inc.	B3	2013-12-05	NBTY, Inc.
Baa1	2013-08-27	Church & Dwight Co., Inc.	B3	2010-11-01	American Achievement Corp
Baa1	2010-10-05	Clorox Company (The)			
Baa1	2009-08-13	Leggett & Platt, Incorporated			
Baa1	2006-10-24	Altria Group Inc.			
Baa2	2008-03-07	Flowers Foods, Inc.			
Baa2	2014-05-19	Kellogg Company			
Baa2	2012-04-26	Molson Coors			
Baa2	2006-01-13	ConAgra Foods, Inc.			
Baa2	2013-06-03	Beam Suntory Inc.			
Baa2	2012-10-23	Reynolds American Inc.			
Baa2	2012-06-14	Hillshire Brands Company			
Baa2	2014-02-14	Whirlpool Corporation			
Baa2	2007-09-05	Hasbro, Inc.			
Baa3	2014-02-27	Mohawk Industries, Inc.			
Baa3	2009-02-05	Newell Rubbermaid, Inc.			
Baa3	2014-05-05	Avon Products, Inc.			
Baa3	2013-09-30	Energizer Holdings, Inc.			
Baa3	2014-01-14	Steelcase Inc.			
Baa3	2011-05-25	Tupperware Brands Corporation			
Ba1	2014-04-29	Constellation Brands, Inc.			
Ba1	2014-05-20	Hanesbrands, Inc.			
Ba1	2013-08-05	Carter's, Inc.			

Table 2 – Oil & Gas Issuers

Aa1	2007-12-17	Chevron Corporation	Baa3	2014-05-22	Weatherford International
Aaa	2010-06-28	XTO Energy	Ba1	2014-02-24	Access Midstream Partners
Aaa	2003-11-15	Exxon Mobil Corporation	Ba1	2014-10-16	Chesapeake Energy Corp.
A1	2005-11-07	ConocoPhillips Company	Ba1	2014-04-28	Cimarex Energy Co.
A1	2012-04-19	Occidental Petroleum Corp.	Ba1	2014-03-18	El Paso Pipeline Partners
A2	2003-11-15	Baker Hughes Incorporated	Ba1	2014-09-02	Energen Corporation
A2	2010-05-03	BJ Services Company	Ba1	2014-07-28	EQT Midstream Partners
A2	2014-09-23	Halliburton Company	Ba1	2010-10-21	Newfield Exploration Company
A2	2012-06-28	Loews Corporation	Ba1	2010-07-02	QEP Resources, Inc.
A2	2013-08-19	National Oilwell Varco, Inc.	Ba1	2014-09-19	Range Resources Corporation
A3	2008-06-24	ANR Pipeline Company	Ba1	2014-05-27	SM Energy Company
A3	2014-08-01	Apache Corporation	Ba1	2014-06-03	Southern Star Central Corp.
A3	2012-04-19	EOG Resources, Inc.	Ba1	2014-10-14	Targa Resources Partners
A3	2014-08-26	Phillips 66	Ba1	2013-06-04	Tesoro Corporation
Baa1	2014-03-11	Cameron International Corp.	Ba2	2008-07-15	AmeriGas Partners
Baa1	2013-03-20	Devon Energy Corp.	Ba2	2013-12-09	Atwood Oceanics, Inc.
Baa1	2012-08-17	El Paso Natural Gas	Ba2	2003-06-13	Bristow Group Inc.
Baa1	2003-11-15	ENSCO International Inc.	Ba2	2013-05-20	Concho Resources Inc.
Baa1	2013-03-08	Enterprise Products Operating	Ba2	2012-04-24	Dresser-Rand Group Inc.
Baa1	2014-05-12	Magellan Midstream Partners	Ba2	2013-09-23	Forum Energy Technologies, Inc.
Baa1	2013-07-31	Marathon Oil Corp.	Ba2	2013-02-27	Kinder Morgan Inc.
Baa1	2011-06-01	Pride International, Inc.	Ba2	2014-10-07	MarkWest Energy Partners
Baa1	2013-08-06	Texas Eastern Transmission	Ba2	2014-04-15	Regency Energy Partners
Baa1	2014-06-16	Transcontinental Gas	Ba2	2013-12-17	Suburban Propane Partners
Baa2	2014-02-10	Boardwalk Pipelines	Ba2	2014-10-20	Tesoro Logistics
Baa2	2013-05-02	Copano Energy	Ba3	2013-10-23	Antero Resources Corp.
Baa2	2013-05-15	DCP Midstream	Ba3	2013-10-16	Crestwood Midstream Partners
Baa2	2012-06-05	FMC Technologies	Ba3	2003-03-24	Denbury Resources Inc.
Baa2	2013-05-02	Kinder Morgan Energy Partners	Ba3	2014-03-31	Exterran Partners
Baa2	2014-05-22	Marathon Petroleum Corp.	Ba3	2013-02-05	Genesis Energy
Baa2	2013-04-10	Nabors Industries Inc.	Ba3	2006-09-22	GulfMark Offshore, Inc.
Baa2	2014-04-23	National Fuel Gas Company	Ba3	2005-02-09	Holly Energy Partners
Baa2	2006-06-06	Noble Energy, Inc.	Ba3	2013-12-17	Linn Energy
Baa2	2006-09-18	ONEOK Partners	Ba3	2013-10-03	NGL Energy Partners
Baa2	2014-04-14	Plains All American Pipeline	Ba3	2014-04-15	PVR Partners
Baa2	2013-11-01	Spectra Energy Partners	Ba3	2014-06-24	Rose Rock Midstream
Baa2	2011-06-14	TC PipeLines	Ba3	2014-05-21	Rosetta Resources Inc.
Baa2	2008-10-08	Valero Energy Corp.	Ba3	2012-12-14	SEACOR Holdings Inc.
Baa3	2014-04-04	Anadarko Petroleum Corp.	Ba3	2013-12-02	Ultra Petroleum Corp.
Baa3	2013-04-30	Buckeye Partners	B1	2011-11-23	Atlas Pipeline Partners
Baa3	2014-03-18	Colorado Interstate	B1	2013-12-30	Basic Energy Services, Inc.
Baa3	2013-12-13	Continental Resources	B1	2012-06-13	Berry Petroleum Company
Baa3	2014-05-19	Enable Midstream Partners, LP	B1	2014-09-05	Bill Barrett Corp
Baa3	2014-03-12	EnLink Midstream Partners, LP	B1	2014-07-25	Breitburn Energy Partners
Baa3	2013-03-21	EQT Corporation	B1	2014-03-26	Calumet Specialty Products Partners
Baa3	2013-06-03	Freeport-McMoRan Oil & Gas	B1	2014-09-15	Carrizo Oil & Gas, Inc.
Baa3	2014-10-01	Murphy Oil Corporation	B1	2014-05-02	Era Group Inc.
Baa3	2014-02-03	ONEOK, Inc.	B1	2011-03-11	EV Energy Partners
Baa3	2012-05-30	Pioneer Natural Resources	B1	2013-04-18	Ferrellgas Partners
Baa3	2012-02-22	Southwestern Energy	B1	2014-01-13	Laredo Petroleum, Inc.
Baa3	2012-10-12	Sunoco Logistics.	B1	2013-02-05	Martin Midstream Partners L.P.
Baa3	2013-11-12	Transocean Inc.	B1	2013-12-13	Parker Drilling Company

B1	2012-08-21	Pioneer Energy Services Corp.
B1	2013-06-03	SemGroup Corporation
B1	2014-07-10	Southcross Energy Partners
B1	2010-10-21	Star Gas Partners
B2	2012-10-17	Alon USA Energy, Inc.
B2	2013-01-07	Alon USA Partners
B2	2014-06-06	ALTA MESA HOLDINGS
B2	2013-06-03	Approach Resources Inc.
B2	2013-04-01	Bonanza Creek Energy, Inc.
B2	2012-04-16	Chaparral Energy, Inc.
B2	2012-05-09	Clayton Williams Energy, Inc.
B2	2013-08-23	Comstock Resources, Inc.
B2	2014-07-22	Diamondback Energy, Inc.
B2	2014-03-12	Energy XXI Gulf Coast, Inc.
B2	2014-05-23	Gulfport Energy Corp.
B2	2013-06-25	Hercules Offshore, Inc.
B2	2012-12-13	Kodiak Oil & Gas Corp
B2	2014-05-07	Legacy Reserves
B2	2013-10-07	Memorial Production Partners
B2	2008-01-14	PDC Energy
B2	2012-05-14	QR Energy,
B2	2012-04-16	Resolute Energy Corp.
B2	2012-12-06	Rex Energy Corp.
B2	2014-09-18	RSP Permian, Inc.
B2	2014-05-23	Sanchez Energy Corp.
B2	2014-06-27	Stone Energy Corp.
B2	2013-08-13	United Refining Company
B2	2012-06-29	W&T Offshore, Inc.
B3	2013-07-11	Atlas Energy,
B3	2014-03-12	EPL Oil & Gas, Inc.
B3	2011-05-18	Forbes Energy Services Ltd.
B3	2014-05-06	Forest Oil Corp.
B3	2013-04-04	Goodrich Petroleum Corp.
B3	2013-04-29	Halcon Resources Corp.
B3	2014-10-08	Magnum Hunter Resources Corp.
B3	2013-04-04	Midstates Petroleum Company Inc.
B3	2014-08-14	Niska Gas Storage Partners LLC
B3	2012-05-07	Northern Oil and Gas, Inc
B3	2013-04-04	Penn Virginia Corp.
B3	2013-06-26	PetroQuest Energy, Inc
B3	2014-02-14	Sabine Oil & Gas
B3	2013-03-07	Seitel, Inc.
B3	2014-07-25	Warren Resources, Inc.

Table 3 – ANOVA Oil & Gas

		Sum of Squares	df	Mean Square	F	Sig.
ROE	Between Groups	960,436	3	320,145	0,398	0,755
	Within Groups	114219,039	142	804,359		
	Total	115179,475	145			
ROA	Between Groups	621,036	3	207,012	5,136	0,002
	Within Groups	5763,428	143	40,304		
	Total	6384,464	146			
ROC	Between Groups	194,066	3	64,689	0,409	0,747
	Within Groups	20568,476	130	158,219		
	Total	20762,541	133			
ROIC	Between Groups	109,993	3	36,664	0,247	0,864
	Within Groups	18876,836	127	148,637		
	Total	18986,828	130			
Gross Margin	Between Groups	2938,368	3	979,456	3,056	0,03
	Within Groups	45184,117	141	320,455		
	Total	48122,485	144			
EBITDA Margin	Between Groups	474,554	3	158,185	0,256	0,857
	Within Groups	87773,56	142	618,124		
	Total	88248,114	145			
Operating Margin	Between Groups	6001,55	3	2000,517	5,215	0,002
	Within Groups	54853,003	143	383,587		
	Total	60854,553	146			
Incremental Operating Margin	Between Groups	421479,365	3	140493,122	1,291	0,28
	Within Groups	15016100,4	138	108812,322		
	Total	15437579,77	141			
Pretax Margin	Between Groups	16380,981	3	5460,327	6,555	0
	Within Groups	119116,392	143	832,982		
	Total	135497,372	146			
Income before XO Margin	Between Groups	12264,275	3	4088,092	5,911	0,001
	Within Groups	98895,08	143	691,574		
	Total	111159,355	146			
Profit Margin	Between Groups	11018,213	3	3672,738	5,431	0,001
	Within Groups	96703,153	143	676,246		
	Total	107721,366	146			
Net Income Margin	Between Groups	11663,34	3	3887,78	6,195	0,001
	Within Groups	89744,235	143	627,582		
	Total	101407,575	146			
Sustainable Growth Rate	Between Groups	1383,179	3	461,06	1,181	0,32
	Within Groups	50380,944	129	390,55		
	Total	51764,123	132			
Cash Ratio	Between Groups	3,338	3	1,113	1,226	0,303
	Within Groups	127,998	141	0,908		
	Total	131,335	144			
Current Ratio	Between Groups	3,602	3	1,201	0,944	0,421
	Within Groups	179,421	141	1,272		
	Total	183,023	144			
Quick Ratio	Between Groups	2,771	3	0,924	0,95	0,418
	Within Groups	137,137	141	0,973		
	Total	139,908	144			
CFO to Current Liab	Between Groups	1,661	3	0,554	0,647	0,586
	Within Groups	120,645	141	0,856		
	Total	122,306	144			
Common Equity to Total Assets	Between Groups	1992,55	3	664,183	2,528	0,06
	Within Groups	37049,488	141	262,762		
	Total	39042,038	144			
Long-Term Debt to Equity	Between Groups	1254244,385	3	418081,462	1,868	0,138
	Within Groups	31563891,72	141	223857,388		
	Total	32818136,1	144			
Long-Term Debt To Capital	Between Groups	8558,811	3	2852,937	8,95	0
	Within Groups	45266,705	142	318,78		
	Total	53825,516	145			
Long-Term Debt to Total Assets	Between Groups	6532,75	3	2177,583	8,886	0
	Within Groups	34799,154	142	245,064		
	Total	41331,904	145			

Total Debt to Equity	Between Groups	1265175,253	3	421725,084	1,867	0,138
	Within Groups	31857603,57	141	225940,451		
	Total	33122778,82	144			
Total Debt to Capital	Between Groups	7719,387	3	2573,129	7,754	0
	Within Groups	47122,723	142	331,85		
	Total	54842,11	145			
Total Debt to Total Assets	Between Groups	5948,587	3	1982,862	8,315	0
	Within Groups	33863,365	142	238,474		
	Total	39811,952	145			
CFO to Total Liabilities	Between Groups	597,174	3	199,058	0,809	0,491
	Within Groups	34950,796	142	246,132		
	Total	35547,971	145			
CFO to CapEx	Between Groups	111,741	3	37,247	0,304	0,822
	Within Groups	17390,018	142	122,465		
	Total	17501,759	145			
Altmans Z Score	Between Groups	15,06	3	5,02	1	0,396
	Within Groups	521,844	104	5,018		
	Total	536,904	107			
Total Debt to EBITDA	Between Groups	201,916	3	67,305	4,616	0,004
	Within Groups	2041,48	140	14,582		
	Total	2243,395	143			
Net Debt to EBITDA	Between Groups	149,384	3	49,795	3,024	0,032
	Within Groups	2305,324	140	16,467		
	Total	2454,708	143			
Total Debt to EBIT	Between Groups	694,051	3	231,35	2,2	0,091
	Within Groups	14405,374	137	105,149		
	Total	15099,425	140			
Net Debt to EBIT	Between Groups	552,091	3	184,03	1,775	0,155
	Within Groups	14206,874	137	103,7		
	Total	14758,965	140			
EBITDA to InterestExpense	Between Groups	93635,585	3	31211,862	0,868	0,459
	Within Groups	4924457,899	137	35944,948		
	Total	5018093,484	140			
EBITDA-CapEx to Interest Expense	Between Groups	33545,203	3	11181,734	2,001	0,117
	Within Groups	760163,133	136	5589,435		
	Total	793708,336	139			
EBIT to Interest Expense	Between Groups	53839,128	3	17946,376	0,996	0,397
	Within Groups	2449687,338	136	18012,407		
	Total	2503526,466	139			
EBITDA to Cash Interest Paid	Between Groups	4313,051	3	1437,684	0,635	0,594
	Within Groups	287582,062	127	2264,426		
	Total	291895,113	130			
EBITDA-CapEx to Cash Interest Paid	Between Groups	97517,431	3	32505,81	3,946	0,01
	Within Groups	1046268,609	127	8238,336		
	Total	1143786,041	130			
EBIT to Cash Interest Paid	Between Groups	2420,661	3	806,887	0,645	0,587
	Within Groups	158754,647	127	1250,037		
	Total	161175,308	130			
Net Debt to Equity	Between Groups	1143766,023	3	381255,341	1,679	0,174
	Within Groups	31780900,91	140	227006,435		
	Total	32924666,94	143			
Net Debt to Capital	Between Groups	6990,409	3	2330,136	4,937	0,003
	Within Groups	66549,293	141	471,981		
	Total	73539,701	144			
EBITDA	Between Groups	849480208,5	3	283160069,5	29,347	0
	Within Groups	1350796780	140	9648548,427		
	Total	2200276988	143			
EBITDA-CapEx	Between Groups	235080793,2	3	78360264,39	14,787	0
	Within Groups	736579697,5	139	5299134,515		
	Total	971660490,7	142			
EBIT	Between Groups	419810314,2	3	139936771,4	25,324	0
	Within Groups	779144745,6	141	5525849,259		
	Total	1198955060	144			
Total Debt	Between Groups	78471,064	3	26157,021	15,712	0
	Within Groups	228081,438	137	1664,828		
	Total	306552,502	140			
Total Assets	Between Groups	3636204,687	3	1212068,229	37,427	0
	Within Groups	4436741,947	137	32384,978		
	Total	8072946,634	140			

Total Equity	Between Groups Within Groups Total	2716373,557 3114876,822 5831250,379	3 137 140	905457,852 22736,327	39,824	0

Table 4 – ANOVA Consumer Products

		Sum of Squares	df	Mean Square	F	Sig.
ROE	Between Groups	7660,689	3	2553,563	3,986	0,011
	Within Groups	44209,156	69	640,712		
	Total	51869,845	72			
ROA	Between Groups	987,485	3	329,162	17,334	0
	Within Groups	1405,25	74	18,99		
	Total	2392,735	77			
ROC	Between Groups	1682,524	3	560,841	12,471	0
	Within Groups	3058,123	68	44,972		
	Total	4740,647	71			
ROIC	Between Groups	2517,416	3	839,139	2,44	0,072
	Within Groups	23730,123	69	343,915		
	Total	26247,539	72			
Gross Margin	Between Groups	1422,761	3	474,254	2,971	0,037
	Within Groups	11651,014	73	159,603		
	Total	13073,775	76			
EBITDA Margin	Between Groups	947,586	3	315,862	5,276	0,002
	Within Groups	4430,324	74	59,869		
	Total	5377,911	77			
Operating Margin	Between Groups	894,393	3	298,131	5,644	0,002
	Within Groups	3908,945	74	52,824		
	Total	4803,338	77			
Incremental Operating Margin	Between Groups	116075,887	3	38691,962	4,006	0,011
	Within Groups	685719,525	71	9658,021		
	Total	801795,411	74			
Pretax Margin	Between Groups	2348,539	3	782,846	13,999	0
	Within Groups	4138,291	74	55,923		
	Total	6486,831	77			
Income before XO Margin	Between Groups	1486,006	3	495,335	13,631	0
	Within Groups	2688,998	74	36,338		
	Total	4175,003	77			
Profit Margin	Between Groups	1441,932	3	480,644	12,719	0
	Within Groups	2796,314	74	37,788		
	Total	4238,246	77			
Net Income Margin	Between Groups	1434,597	3	478,199	12,643	0
	Within Groups	2798,863	74	37,822		
	Total	4233,46	77			
Sustainable Growth Rate	Between Groups	2601,713	3	867,238	1,158	0,332
	Within Groups	50932,939	68	749,014		
	Total	53534,652	71			
Cash Ratio	Between Groups	0,005	3	0,002	0,015	0,998
	Within Groups	8,276	74	0,112		
	Total	8,281	77			
Current Ratio	Between Groups	9,712	3	3,237	6,114	0,001
	Within Groups	39,181	74	0,529		
	Total	48,894	77			
Quick Ratio	Between Groups	0,901	3	0,3	1,485	0,226
	Within Groups	14,972	74	0,202		
	Total	15,874	77			
CFO to Current Liab	Between Groups	0,085	3	0,028	0,329	0,804
	Within Groups	6,378	74	0,086		
	Total	6,463	77			
Common Equity to Total Assets	Between Groups	1747,665	3	582,555	1,282	0,287
	Within Groups	33618,413	74	454,303		
	Total	35366,078	77			

Long-Term Debt to Equity	Between Groups	307236,644	3	102412,215	0,875	0,458
	Within Groups	8305964,518	71	116985,416		
	Total	8613201,162	74			
Long-Term Debt To Capital	Between Groups	12875,747	3	4291,916	5,629	0,002
	Within Groups	56422,123	74	762,461		
	Total	69297,871	77			
Long-Term Debt to Total Assets	Between Groups	6246,808	3	2082,269	9,506	0
	Within Groups	16209,579	74	219,048		
	Total	22456,387	77			
Total Debt to Equity	Between Groups	326967,265	3	108989,088	0,606	0,613
	Within Groups	12772375,65	71	179892,615		
	Total	13099342,92	74			
Total Debt to Capital	Between Groups	8139,79	3	2713,263	3,049	0,034
	Within Groups	65858,282	74	889,977		
	Total	73998,071	77			
Total Debt to Total Assets	Between Groups	4028,215	3	1342,738	5,119	0,003
	Within Groups	19410,54	74	262,305		
	Total	23438,755	77			
CFO to Total Liabilities	Between Groups	3118,088	3	1039,363	13,271	0
	Within Groups	5795,538	74	78,318		
	Total	8913,626	77			
CFO to CapEx	Between Groups	296,972	3	98,991	1,091	0,358
	Within Groups	6712,535	74	90,71		
	Total	7009,507	77			
Altmans Z Score	Between Groups	29,179	3	9,726	4,904	0,004
	Within Groups	128,927	65	1,983		
	Total	158,106	68			
Total Debt to EBITDA	Between Groups	49,988	3	16,663	2,288	0,086
	Within Groups	538,936	74	7,283		
	Total	588,924	77			
Net Debt to EBITDA	Between Groups	119,868	3	39,956	16,465	0
	Within Groups	179,574	74	2,427		
	Total	299,442	77			
Total Debt to EBIT	Between Groups	502,513	3	167,504	11,54	0
	Within Groups	1074,131	74	14,515		
	Total	1576,644	77			
Net Debt to EBIT	Between Groups	473,463	3	157,821	10,671	0
	Within Groups	1094,456	74	14,79		
	Total	1567,919	77			
EBITDA to InterestExpense	Between Groups	4135,54	3	1378,513	2,354	0,08
	Within Groups	40413,559	69	585,704		
	Total	44549,099	72			
EBITDA-CapEx to Interest Expense	Between Groups	2665,262	3	888,421	2,284	0,087
	Within Groups	26841,875	69	389,013		
	Total	29507,136	72			
EBIT to Interest Expense	Between Groups	3258,794	3	1086,265	2,374	0,078
	Within Groups	31568,771	69	457,518		
	Total	34827,564	72			
EBITDA to Cash Interest Paid	Between Groups	17278,973	3	5759,658	1,765	0,161
	Within Groups	234923,138	72	3262,821		
	Total	252202,111	75			
EBITDA-CapEx to Cash Interest Paid	Between Groups	12578,556	3	4192,852	1,743	0,166
	Within Groups	173160,488	72	2405,007		
	Total	185739,044	75			
EBIT to Cash Interest Paid	Between Groups	13494,774	3	4498,258	1,767	0,161
	Within Groups	183278,567	72	2545,536		
	Total	196773,341	75			
Net Debt to Equity	Between Groups	221907,049	3	73969,016	0,494	0,688
	Within Groups	10638182,57	71	149833,557		
	Total	10860089,62	74			
Net Debt to Capital	Between Groups	8529,104	3	2843,035	2,947	0,038
	Within Groups	71390,612	74	964,738		
	Total	79919,716	77			
EBITDA	Between Groups	169598381	3	56532793,66	5,815	0,001
	Within Groups	719475803,4	74	9722645,992		
	Total	889074184,4	77			
EBITDA-CapEx	Between Groups	105005711	3	35001903,67	5,255	0,002
	Within Groups	492916104,1	74	6661028,434		
	Total	597921815,1	77			

EBIT	Between Groups	117632299,9	3	39210766,63	5,365	0,002
	Within Groups	540789599,9	74	7307967,566		
	Total	658421899,8	77			
Total Debt	Between Groups	40878,331	3	13626,11	3,107	0,032
	Within Groups	324516,107	74	4385,353		
	Total	365394,437	77			
Total Assets	Between Groups	484086,049	3	161362,016	3,653	0,016
	Within Groups	3269093,808	74	44176,943		
	Total	3753179,857	77			
Total Equity	Between Groups	246715,803	3	82238,601	3,797	0,014
	Within Groups	1602935,844	74	21661,295		
	Total	1849651,647	77			

Table 5 – ANOVA Complete Model

		Sum of Squares	df	Mean Square	F	Sig.
ROE	Between Groups	11283,618	3	3761,206	4,919	,003
	Within Groups	164395,664	215	764,631		
	Total	175679,281	218			
ROA	Between Groups	1899,257	3	633,086	19,004	,000
	Within Groups	7362,363	221	33,314		
	Total	9261,620	224			
ROC	Between Groups	1216,909	3	405,636	3,336	,020
	Within Groups	24559,818	202	121,583		
	Total	25776,727	205			
ROIC	Between Groups	1229,051	3	409,684	1,849	,140
	Within Groups	44314,443	200	221,572		
	Total	45543,493	203			
Gross Margin	Between Groups	2844,555	3	948,185	3,269	,022
	Within Groups	63224,733	218	290,022		
	Total	66069,288	221			
EBITDA Margin	Between Groups	1407,360	3	469,120	,912	,436
	Within Groups	113171,132	220	514,414		
	Total	114578,491	223			
Operating Margin	Between Groups	4551,044	3	1517,015	5,431	,001
	Within Groups	61731,678	221	279,329		
	Total	66282,722	224			
Incremental Operating Margin	Between Groups	238204,853	3	79401,618	1,050	,372
	Within Groups	16112635,739	213	75646,177		
	Total	16350840,591	216			
Pretax Margin	Between Groups	15885,083	3	5295,028	9,278	,000
	Within Groups	126131,598	221	570,731		
	Total	142016,681	224			
Income before XO Margin	Between Groups	11652,724	3	3884,241	8,277	,000
	Within Groups	103711,968	221	469,285		
	Total	115364,692	224			
Profit Margin	Between Groups	10693,653	3	3564,551	7,776	,000
	Within Groups	101303,226	221	458,386		
	Total	111996,879	224			
Net Income Margin	Between Groups	11687,115	3	3895,705	9,162	,000
	Within Groups	93973,717	221	425,220		
	Total	105660,832	224			
Sustainable Growth Rate	Between Groups	3538,886	3	1179,629	2,268	,082
	Within Groups	104539,803	201	520,099		
	Total	108078,690	204			
Cash Ratio	Between Groups	2,457	3	,819	1,307	,273
	Within Groups	137,237	219	,627		
	Total	139,695	222			
Current Ratio	Between Groups	4,467	3	1,489	1,380	,250
	Within Groups	236,308	219	1,079		
	Total	240,775	222			
Quick Ratio	Between Groups	3,276	3	1,092	1,567	,198
	Within Groups	152,613	219	,697		
	Total	155,888	222			
CFO to Current Liab	Between Groups	5,678	3	1,893	2,738	,044
	Within Groups	151,381	219	,691		
	Total	157,059	222			

Common Equity to Total Assets	Between Groups	1328,347	3	442,782	1,263	,288
	Within Groups	76746,909	219	350,443		
	Total	78075,256	222			
Long-Term Debt to Equity	Between Groups	1012034,102	3	337344,701	1,802	,148
	Within Groups	40428786,474	216	187170,308		
	Total	41440820,576	219			
Long-Term Debt To Capital	Between Groups	16007,125	3	5335,708	10,899	,000
	Within Groups	107700,774	220	489,549		
	Total	123707,899	223			
Long-Term Debt to Total Assets	Between Groups	12502,167	3	4167,389	17,705	,000
	Within Groups	51783,289	220	235,379		
	Total	64285,456	223			
Total Debt to Equity	Between Groups	869361,830	3	289787,277	1,378	,250
	Within Groups	45412907,380	216	210244,942		
	Total	46282269,210	219			
Total Debt to Capital	Between Groups	9154,478	3	3051,493	5,456	,001
	Within Groups	123053,386	220	559,334		
	Total	132207,864	223			
Total Debt to Total Assets	Between Groups	8186,093	3	2728,698	10,902	,000
	Within Groups	55063,942	220	250,291		
	Total	63250,035	223			
CFO to Total Liabilities	Between Groups	994,589	3	331,530	1,595	,191
	Within Groups	45720,744	220	207,822		
	Total	46715,333	223			
CFO to CapEx	Between Groups	222,764	3	74,255	,665	,575
	Within Groups	24577,569	220	111,716		
	Total	24800,333	223			
Altmans Z Score	Between Groups	101,081	3	33,694	8,045	,000
	Within Groups	724,557	173	4,188		
	Total	825,638	176			
Total Debt to EBITDA	Between Groups	299,094	3	99,698	8,268	,000
	Within Groups	2628,698	218	12,058		
	Total	2927,792	221			
Net Debt to EBITDA	Between Groups	316,934	3	105,645	9,168	,000
	Within Groups	2512,031	218	11,523		
	Total	2828,965	221			
Total Debt to EBIT	Between Groups	1503,964	3	501,321	6,856	,000
	Within Groups	15721,927	215	73,125		
	Total	17225,890	218			
Net Debt to EBIT	Between Groups	1287,516	3	429,172	5,915	,001
	Within Groups	15600,002	215	72,558		
	Total	16887,518	218			
EBITDA to InterestExpense	Between Groups	56677,112	3	18892,371	,790	,501
	Within Groups	5020205,331	210	23905,740		
	Total	5076882,443	213			
EBITDA-CapEx to Interest Expense	Between Groups	42819,599	3	14273,200	3,727	,012
	Within Groups	800479,412	209	3830,045		
	Total	843299,011	212			
EBIT to Interest Expense	Between Groups	35015,353	3	11671,784	,973	,406
	Within Groups	2506639,440	209	11993,490		
	Total	2541654,794	212			
EBITDA to Cash Interest Paid	Between Groups	4354,696	3	1451,565	,546	,651
	Within Groups	539787,730	203	2659,053		
	Total	544142,426	206			
EBITDA-CapEx to Cash Interest Paid	Between Groups	113712,217	3	37904,072	6,029	,001
	Within Groups	1276278,830	203	6287,088		
	Total	1389991,047	206			
EBIT to Cash Interest Paid	Between Groups	5507,687	3	1835,896	1,053	,370
	Within Groups	353875,008	203	1743,227		
	Total	359382,695	206			
Net Debt to Equity	Between Groups	900836,011	3	300278,670	1,505	,214
	Within Groups	42886878,267	215	199473,852		
	Total	43787714,278	218			
Net Debt to Capital	Between Groups	12011,372	3	4003,791	6,193	,000
	Within Groups	141588,686	219	646,524		
	Total	153600,059	222			
EBITDA	Between Groups	803684535,686	3	267894845,229	25,484	,000
	Within Groups	2291692360,068	218	10512350,276		
	Total	3095376895,754	221			

EBITDA-CapEx	Between Groups	368558879,478	3	122852959,826	21,093	,000
	Within Groups	1263891978,026	217	5824386,996		
	Total	1632450857,504	220			
ROE	Between Groups	478614353,939	3	159538117,980	25,085	,000
	Within Groups	1392823347,140	219	6359923,960		
	Total	1871437701,079	222			
ROA	Between Groups	123380,692	3	41126,897	15,936	,000
	Within Groups	554859,113	215	2580,740		
	Total	678239,805	218			
ROC	Between Groups	2941907,531	3	980635,844	23,729	,000
	Within Groups	8885144,751	215	41326,255		
	Total	11827052,282	218			
ROIC	Between Groups	1878408,843	3	626136,281	23,191	,000
	Within Groups	5804838,427	215	26999,248		
	Total	7683247,270	218			