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The Determinants of Creditworthiness

An Empirical Study of the Relationship Between Credit Ratings and Financial Ratios in the E&P Industry

Brage Herje Bergrem

Supervisor: Roar Os Ådland

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Abstract

This thesis investigates the usefulness of financial ratios in explaining the variation observed in Standard and Poor's credit ratings within the E&P industry. Culminating from a cross-sectional study of 82 E&P companies at year-end 2012, we propose a multinomial logit model consisting of three financial ratios that correctly classifies the ratings of 59.8 and 49.4 percent of in-sample and out-of-sample observations, respectively. If the model is reduced to only classify ratings as investment grade and speculative grade, the share of correctly classified ratings increases to 84.1 and 83.1 percent. The three retained ratios are Net Debt Ratio, Coverage Ratio and Cash Flow per BOE. Our analysis implies that a non-linear model with only three financial ratios captures a considerable share of the determinants of credit ratings among E&P companies.

Acknowledgements

This thesis was written as a part of the Master of Science in Financial Economics at the Norwegian School of Economics (NHH). Due to a great interest in the international oil and gas industry, I have tried to tailor my degree at NHH to encompass both finance- and petroleum-related courses. A natural extension of this choice was to collaborate with an E&P company when writing my final thesis, and I feel fortunate to have gotten the chance to collaborate with Statoil's Enterprise Risk Management department. Throughout the process they have taken the time to give me invaluable feedback which has both improved the quality of this thesis and expanded my knowledge about Enterprise Risk Management and the E&P industry. In particular, I would like to thank Nicolay Wærp at Statoil for setting aside considerable time for discussions. I could not be more grateful for his support.

The initial topic for this thesis was not that of the relationship between financial ratios and credit ratings. Rather, Statoil's suggestion related to the usefulness of financial ratios in operationalizing an E&P company's appetite for profit and financial robustness. In order to analyze such a topic empirically, there is a need to obtain a quantitative proxy for E&P companies' ambitions for profit and financial robustness. Publicly available information did not suffice in creating this proxy, and the dependent variable thus had to be changed. Nevertheless, I believe that the methodology used to analyze financial ratios empirically in this thesis can be applied to the initial topic – as long as a good proxy can be constructed.

I would like to thank Professor Roar Os Ådland for providing excellent feedback before and during the writing process. Finally, I would like to thank Professor Håkan Jankensgård at Lund University for his helpful comments during the initial stages of this process. Any errors are the sole responsibility of the author. For interested readers, the data set used to conduct the analyses is available on request.

June 2014, Bergen

Brage Herje Bergrem

Preface Statoil ASA

Statoil

Brage approached Statoil with the interest of writing a topic within the field of Enterprise Risk Management. We responded by suggesting a thesis relating to ¨a company's appetite for profit and financial robustness expressed by different threshold levels¨. This is a very lofty and abstract topic as such, however Brage was inspired to explore into this vast field and started to collect data that expresses profit and financial robustness. After processing the data Brage came up with the more definite idea of testing the relationship between credit ratings and financial ratios within a PCA framework. The result of the empirical study sheds interesting light on the relationship, and could spur our own work in establishing different threshold levels expressing the appetite for profit and financial robustness.

Best regards,

Nicolay Wærp
Enterprise Risk Management
Statoil ASA

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1. Introduction

Every year corporations disclose a plethora of financial information in their respective annual reports. The use of financial ratios for the purpose of comparing this information across corporations has become widespread among both academics and practitioners, but what do these ratios actually convey? Are some ratios more convenient to use in certain industries compared to others? Does a combination of financial ratios encapsulate enough appropriate information to explain an inherently complex phenomenon in a simple, yet robust way?

In this thesis, Standard and Poor's (S&P's) long term credit ratings assigned to companies within the exploration and production (E&P) industry will be the complex phenomenon in question. Credit ratings are opinions of creditworthiness and emerge from thorough analyses that are based on substantial amounts of both quantitative and qualitative data. Additionally, the credit rater's subjective judgement is considered important in arriving at corporate bond ratings[1]. Consequently, understanding what a credit rating actually contains is by no means straightforward, although the simple nature of the nine-point alphabetical rating scale might suggest otherwise.

The purpose of this thesis is to investigate the usefulness of financial ratios in explaining the variation observed in credit ratings within the E&P industry. The choice to focus on the explanatory power of financial ratios is related to a subtlety that has fascinated me throughout my studies – Variation in industry characteristics is enormous compared to the variation in financial ratios used to convey key information in these industries. Due to vastly different industry characteristics, it is hard to imagine that the insight provided by a financial ratio is equal across industries – a financial ratio is likely to have greater "utility" in certain industries compared to others.

Imagination is more or less the only constraint when it comes to constructing financial ratios, because any two items in a financial statement can form a ratio. However, the only ratios eligible for inclusion in this study are either ratios that are classified as "key figures" in Statoil ASA's peer group or ratios explicitly deemed important in S&P's rating

[1] See Pogue and Soldofsky (1969).

methodology. We choose to impose these criteria because it is desirable to evaluate the usefulness of ratios that are already commonly used among influential companies in the E&P industry. Statoil ASA's peer group includes Anadarko, BG, BP, Chevron, ConocoPhillips, Devon Energy, Encana, Eni, Exxon, Lukoil, Occidental, Petrobras, Royal Dutch Shell, Repsol, Statoil and Total, and the "key figures" in these companies annual reports from 2012 provide the basis for the financial ratios included in this study. In addition the two core debt-payback ratios used in S&P's Corporate Rating Criteria are included: Funds from Operations (FFO)/Debt and Debt/EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortisation)[2]. Finally, E&P-specific financial ratios classified as important by S&P are included: Reserves Replacement Ratio and Average Reserve Life Index. The main hypothesis in this thesis is that these latter four financial ratios are the most important when it comes to explaining the variation in S&P's credit ratings within the E&P industry.

This thesis contributes to the existing literature in two ways. First, this is to our knowledge the first study of the relationship between credit ratings and financial ratios that specifically addresses the E&P industry. Due to our hypothesis about ratios' differing "utility" across industries, we believe that a study focusing solely on the E&P industry can provide valuable insight about the relationship between financial ratios and credit ratings to both investors and E&P companies. Second, we are not aware of any studies that select financial ratios solely from "key figures" in annual reports. When it comes to the determinants of credit ratings, our study will evaluate which of these ratios is truly influential.

This thesis is organized as follows: chapter 2 provides information on the rationale behind credit ratings, the rating process and a literature review of the link between credit ratings and financial ratios. Chapter 3 elaborates on the data selection procedure and the screening process. Chapter 4 summarizes the methodology used in answering the research problem and chapter 5 presents our findings. Limitations and possible future research are discussed in chapter 6. Chapter 7 concludes.

[2] http://www.standardandpoors.com/prot/ratings/articles/en/us/?articleType=HTML&assetID=1245366688415 Paragraph 245.

2. Theory

Information on the relationship between credit ratings and financial ratios can partly be obtained from both credit rating agencies' (hereby denoted CRA's) disclosures and publications from external parties. This chapter seeks to provide a brief summary of the theory that serves as a foundation for our forthcoming analyses.

2.1 Credit Ratings

2.1.1 Purpose of- and Rationale Behind Credit Ratings

Whenever a party decides to engage in a lending transaction, the ultimate goal is normally to earn a sufficient profit on the capital allocated for that transaction. Whether or not a sufficient profit is made obviously depends on the counterparty's ability to repay the loan. Thus, in-depth information about the counterparty's ability (or willingness) to repay becomes extremely valuable to the lender when deciding on which borrowers to allocate capital to. If the lender must conduct thorough analyses on all potential borrowers, transaction costs will increase. Assuming no information sharing among lenders, the aggregated costs associated with counterparty assessment can become substantial.

In the bond market, where the issuer often wishes to obtain capital from both institutional and private lenders, CRA's collect information about a large number of issuers and the bonds that they have issued (see White (2013) for a thorough discussion). This information culminates in an assigned credit rating that serves as a third party opinion on the creditworthiness of the issuer (or of a specific issue). Provided that the ratings assigned by the CRA's can be trusted[3], these opinions can reduce the transaction costs among lenders because additional analyses on creditworthiness done by the lenders may become redundant. Reduced transaction costs will increase the attractiveness of buying bonds, and issuers will therefore tend to incur increased access to external funding. Consequently, reliable credit ratings will likely benefit both issuers and lenders in the bond market.

[3] There are several examples of unaccurate credit ratings: Enron were rated as Investment Grade five days before their bankruptcy. Lehman Brothers were rated as Investment Grade the morning of their bankruptcy (White 2013).

When credit ratings were introduced for the first time in 1909, the lenders were the ones paying for the rating services (White, 2013). After the bankruptcy of Penn Central Railroad in the 1970s, however, the need for more transparency in credit ratings became obvious[4], and the business model shifted to an "issuer pays"-model. Today, information on credit ratings is available for free to all potential lenders at the issuers' expense.

Why are credit ratings important to companies? If a company chooses to obtain funding through the debt market, a lower rating will, assuming that the opinions of the CRA's are shared with lenders, increase the cost of that external funding through a higher risk premium.

Although there are a number of CRA's offering opinions on creditworthiness of issuers, Standard & Poor's (S&P), Moody's and Fitch are characterized as the three dominant players in the credit rating industry (White, 2013). In this thesis, the focus will be on S&P's ratings mainly due to convenience when it comes to data collection[5]. A rating issued by S&P is a forward-looking opinion about the creditworthiness of issuers and obligations, where the term creditworthiness refers to the question of whether a bond or another financial instrument will be paid according to its contractual terms[6]. Different credit ratings indicate different abilities to withstand economic stress without defaulting.

Even though the rank ordering of ratings appears straightforward, there are several underlying dimensions encapsulated in a rating. In S&P's view, the likelihood of default (LD) is the centrepiece of creditworthiness, and therefore the centrepiece of credit ratings[4]. If an issuer can withstand a very stressful economic environment without defaulting, it should, according to the likelihood of default criterion, be assigned a rating within the highest categories. However, secondary factors can lead to a lower rating than the LD criterion suggests and vice versa. One such factor is the credit stability of the issuer – there are issuers which default without any warning, but other issuers experience a gradual deterioration before defaulting[4].

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[4] https://www.globalcreditportal.com/ratingsdirect/renderArticle.do?articleId=1182922&SctArtId=185309&from=CM&nsl_code=LIME

[5] Datastream do not offer historical credit ratings for other CRA's than S&P.

[6] Key Attributes Of Standard & Poor's Credit Ratings, available on www.standardandpoors.com

S&P aspire to have comparability in credit ratings across industries, that is, an A-rating in one industry should ideally indicate the same level of creditworthiness as an A-rating in another industry. However, different industry characteristics often lead to varying degrees of economic stress in a given situation. For example, a credit crisis could impose a great deal of economic stress in the banking industry and for entrepreneurial companies seeking funding, but need not affect established industrial companies so profoundly[7]. To account for such industry characteristics, S&P publish specific criteria for creditworthiness assessment in different industries.

2.1.2 S&P's Key Credit Factors for the E&P Industry

In order to help market participants better understand S&P's approach to reviewing key credit factors in the E&P industry[8], a detailed publication is issued on S&P's website. The most important aspects will be presented in this subchapter. Methodologically, the publication elaborates on both industry- and company criteria that affects the final opinion of creditworthiness among E&P companies. Industry criteria address issues that are systemic for the E&P sector, that is, issues that typically affect the entire industry. These are divided into the categories *Cyclicality* and *Competitive risk and growth.*

If an industry is not affected by the business cycle, the creditworthiness of companies within that sector is likely to remain relatively stable in times of economic turmoil. S&P believe that the higher level of profitability cyclicality in an industry, the higher the credit risk of companies in that industry[8]. Due to the importance of crude oil and natural gas in the world's energy markets, and the importance of energy to the economy in general, the E&P industry is often characterized as cyclical – the industry is fluctuating with the overall economy. S&P assess the cyclicality in the E&P industry as moderately high risk[8]. To assess the Competitive risk and growth, barriers to entry, industry profit margins, risk of substitutes (new products, services and technologies) and risk in growth trends are analyzed[8]. S&P argue that the E&P industry warrants an intermediate competitive risk and growth

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[7] An example is the Dot-Com Crisis. http://www.dn.no/nyheter/2009/06/11/-kall-det-en-realokonomisk-krise

[8] Information in this subchapter is mainly extracted from the publication *Key Credit Factors For The Oil And Gas Exploration And Production Industry.*
https://www.globalcreditportal.com/ratingsdirect/renderArticle.do?articleId=1227034&SctArtId=201625&from=CM&nsl_code=LIME

assessment[8]. Combined, the assessment on these two categories provides insight into the issues S&P deem influential for the E&P industry in general.

Since our study only contains companies within the E&P industry, all companies will be exposed to these industry issues to some extent. Consequently, the company specific criteria are primarily the ones of interest in our study.

First, companies' creditworthiness can differ due to country risk – Some areas are inherently more risky to allocate capital to than others. Several companies within Statoil's peer group state that country risk is a critical risk factor[9]. S&P assess various companies' exposure to country risk through the EBITDA they generate in each country. As a result, two companies that in isolation appear to express the same creditworthiness may end up with different credit ratings due to their different exposure to country risk.

Second, the competitive position of a company within the E&P industry can significantly affect its creditworthiness. S&P use four dimensions to evaluate a firm's competitive position:

- *Competitive advantage.* According to S&P, the management of risks related to replacing and increasing reserves largely determines the competitive advantage of a company[8]. Hereunder, growth potential of operating areas, the mix between oil and gas liquids[10], regional differences in revenue (due to differing qualities of oil and/or transportation costs) and diversification[8] together give an impression of an E&P company's competitive advantage.
- *Scale, scope and diversity.* Predominantly this dimension addresses the characteristics of a company's reserves – size of the reserves, whether reserves stem from onshore or offshore operations, geographic diversity of production sources and current production and growth prospects[8]. Financial ratios used by S&P when

[9] In the companies' respective annual reports from 2012, Statoil, Royal Dutch Shell, Chevron, Total, Petrobras and ENI all state country risk as an important risk factor.

[10] For European E&P companies, this is an interesting point. S&P argue that the creditworthiness increases if a company that operates in an area where the correlation between oil and gas prices is low has a balanced mix between oil and gas liquids. This is the case in the US, but the prices on the European gas market have historically been tied closely to oil. Now the gas market is changing in this respect. E&P companies in Europe can therefore be perceived as more creditworthy in the future if they have a mix between oil and gas liquids and the correlation between the prices on these products decreases.

assessing this dimension include Reserve Life Index, Reserve Replacement Ratio and Proved Developed Producing Ratio.

- *Operating Efficiency.* S&P view finding and development costs (hereby denoted F&D costs) as the best measure of a company's organic growth capabilities[8]. Since lower F&D costs indicate higher operating margins and a larger cash flow, the need for external funding is likely to be smaller. In isolation, this effect is likely to improve the creditworthiness of a company. Because E&P companies are price takers, the efficiency with regards to F&D costs is critical when determining a company's competitive position.
- *Profitability.* When assessing profitability, S&P take both the level and the volatility into consideration. Profitability ratios used are among others Return on Capital and EBI Margin, and every rated E&P company gets ranked annually at a three point scale: Above average, average and below average[8]. The volatility of profitability is assessed using seven years of historical data in a regression model.

Following a review of the first three dimensions discussed above, S&P assign weights to these categories: Competitive advantage's relative importance is 10 percent, scale, scope and diversity 55 percent and operating efficiency 35 percent. Applying these weights creates a preliminary competitive position for each rated company within the E&P industry. The profitability dimension is then used to make adjustments to this position if necessary.

Although somewhat simplified, this review highlights the most important aspects of S&P's rating procedure that specifically apply to E&P companies. In our research the financial ratios used to evaluate these criteria are very interesting – we would expect these ratios to account for more variation in credit ratings than other financial ratios that are not used explicitly by S&P.

2.2 Literature Review

Financial ratios and credit ratings are in and of themselves two prominent constituents in financial economics. Over the course of time there have been a large number of studies conducted on both, but the relationship between them is a somewhat unilluminated field in the literature. This subchapter aims to give a review of the relatively modest amount of research conducted in this field. Methodologically, the multivariate techniques used in this thesis are inspired by this research, although not entirely equal.

Horrigan (1966) published the first study that investigated the link between bond ratings and financial ratios (Pinches & Mingo, 1973). Using a sample consisting of American manufacturing firms, Horrigan tries to predict ratings from both S&P and Moody's by relying exclusively on financial ratios. Independent variables (financial ratios) are selected subjectively[11] and subsequently included in a multiple regression. The conclusion is that a multiple regression model that includes six variables can predict approximately 58 percent of Moody's and 52 percent of S&P's new bond ratings in the sample[12].

Pogue and Soldofsky (1969) question to what extent qualitative assessments based on judgments affect credit ratings compared to quantifiable financial ratios by investigating the top four rating categories issued by Moody's, and find that five financial ratios in a linear model account for 80 percent of the variation in credit ratings in the original sample[13]. How these five independent variables were selected is not elaborated on in the publication.

Using a total of 180 bonds, Pinches and Mingo (1973) obtain a different approach. Instead of selecting independent variables somewhat arbitrarily, the data set is screened through factor analysis. The goal of this procedure is to reduce the dimensionality of the data set without losing much of the initial variation within the sample. This is done by transforming the initial independent variables to orthogonal factors. Only one variable from each of the five factors that explain most of the variation in the data set is then selected as independent variables for a subsequent Multiple Discriminant Analysis. The exact criteria for variable selection are not disclosed, but the retained variables are issue size, long-term debt to total assets, net income to total assets, years of consecutive dividends, net income plus interest to interest and a dummy variable for subordination status (Pinches & Mingo,

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[11] The financial ratios and other variables most highly correlated with the bond ratings were initially selected as the best variables. Highly intercorrelated variables were then eliminated from the regression equation based on the author's judgments (Horrigan 1966).

[12] The variables used were subordination (dummy variable), working capital/sales, sales/net worth, total assets, net worth/total debt and net operating profit/sales.

[13] Contrary to Horrigan's study, Pogue and Soldofsky use a dichotomous dependent variable to predict whether a company should be in one of two rating classes (for example Aaa or Aa).

1973). In the original sample, the model correctly predicts close to 70 percent of the actual ratings.

Kaplan and Urwitz (1979) argue that while constructing statistical models for predicting bond ratings is of interest, previous research does not take into account the strong assumptions that underlie the multivariate techniques used. One example of this is the fact that Ordinary Least Squares (OLS) treats credit ratings as a continuous variable. Essentially, this implies that the distance between AA and A is equal to the distance between BB and B. There is no obvious reason for such an assumption to hold. To account for this and several other methodology-related issues in previous studies, Kaplan and Urwitz introduce a multivariate probit model that treats the dependent variable as ordinal. In order to compare the usefulness of the multivariate probit model with an OLS-procedure, the model from the Horrigan study is used with a more recent sample. Contrary to prior belief, Kaplan and Urwitz find that the OLS-procedure performs marginally better than the probit model for the sample in question.

Laitinen (1999) uses multinomial logistic regression and regular linear regression to investigate how much of the variation in corporate risk estimates assigned to Finnish companies by the rating agency Finska can be explained by the information in the agency's database. Essentially, Laitinen argues that these corporate risk estimates encapsulate both information from this database and information from the credit analyst's own investigations. The hypothesis is that if the credit analyst does not use his own judgments (here: information from his own investigations), the corporate risk estimates can be perfectly replicated by statistical models. In Laitinen's study, in- and out-of-sample tests yield 96 and 90 percent prediction accuracy respectively, suggesting that subjective judgments by analysts do not affect the assigned ratings to a very large extent.

Doumpos and Pasiouras (2005) point out that the majority of research on ratings has focused on large CRA's. Consequently, they highlight the need to increase the body of literature on the determinants of credit ratings assigned by regional or specialized agencies. Using ratings issued by Qui Credit Assessment Ltd., a UK credit rating agency, they introduce a model of 10 financial ratios that classifies just over 72 percent of the cases in their sample correctly.

Of the more recent work, Amdouni and Soumare (WP) highlight the need for a model that can be used as a tool by corporations to replicate ratings assigned by CRA’s. Using a sample of Canadian non-financial corporations they attempt to identify the main determinants of S&P’s ratings, as well as examining whether it is possible to replicate and predict external ratings with good reliability (Amdouni & Soumare, WP). Utilizing a Multinomial Logit model, the model yields a predictive power of 71.5 and 61.3 percent for overall in- and out-of-samples respectively. The total number of independent variables is seven, and these are included based on a multinomial logit regression for each potential independent variable. Variables with large values on a Wald test are considered for inclusion in the main model.

To summarize, widely varying methodologies have been undertaken when creating statistical models for either explaining or predicting bond ratings. It does not appear to be a clear consensus with regards to which methodology to use. One explanation can be that different samples used can have vastly different characteristics. For example, an OLS-procedure on a sample that does not have issues with the assumptions of normality and homoscedasticity can very well yield relatively robust results even if the dependent variable is treated as continuous. However, this need not be the case when the same model is used on a sample with vastly different characteristics. The key takeaway must therefore be that a thorough assessment of the sample’s characteristics is necessary to select a methodology that has a chance of producing unbiased and robust results.

3. Data

Previous studies of the link between credit ratings and financial ratios have not so much delved into potential differences across industries as they have aspired to establish a comprehensive link across a number of industries. A comprehensive approach gives more leeway with regards to data collection, because the defined population is not industry specific. Any attempt to find an industry specific link between credit ratings and financial ratios needs to deal with the fact that the target population is vastly smaller. This chapter seeks to convey an introduction to the data set used in the subsequent analyses. Consequently, information on both data selection and the data screening process will be presented in the coming subchapters. We believe the characteristics of the data set significantly affect the attractiveness of multivariate techniques. As a result, the data selection and screening will be conducted prior to deciding on which methodology to use. Quantitatively, we believe the forthcoming analyses will be substantially more robust using such an approach.

3.1 Data Selection

3.1.1 Sample

The target population in this study is companies rated by S&P that have operations in the E&P segment. The sample, defined as a representative portion of the population which is selected for study (Burns & Burns, 2008, p. 181), needs to represent this underlying population as accurately as possible.

Even if a company fulfills every criterion to be classified as an E&P company, it will not be eligible for inclusion in our sample unless it is assigned a rating by S&P. The raw sample therefore includes all companies rated by S&P within the energy sector. Listings of rated companies sorted by sectors are available for registered users on the S&P website. In its current form, the sample includes a number of companies that do not have operations within the E&P segment. These companies will yield a substantial sampling error if they are kept in the sample, and are thus eliminated. North American companies are kept in the sample if they have Standard Industrial Classification (SIC) code 1311 (Crude Petroleum and Natural Gas) or 2911 (Petroleum Refining)[14]. For companies outside North America, elimination is achieved through a criteria search in the companies' 2012 annual reports. Retaining only companies that have E&P operations causes the sample size to plunge from 324 to 175 companies.

For data collection purposes, companies that are not publicly listed are eliminated from the sample, yielding a sample reduction of 21 companies. Additionally, a number of E&P companies that are rated by S&P have either been part of a merger or are no longer in business. To account for this, the sample is refined by filtering out the companies which do not have an active equity status. Information on equity status is easily obtained through Datastream, and after filtering the sample consists of 131 E&P companies.

3.1.2 Dependent Variable

Because annual reports for 2013 were not published by the time of this analysis, the financial ratios included are calculated for December 31st 2012. Assuming a zero lag-lead relationship between credit ratings and financial ratios, the appropriate credit ratings to use as a dependent variable are those of December 31st 2012.

A total of four different credit ratings are typically assigned by S&P to each company – foreign long term, foreign short term, local long term and local short term. Our sample includes companies from every continent, thus foreign ratings are therefore preferred. Furthermore, the following analyses will use long term credit ratings. This corresponds to previous research on credit ratings in regression contexts conducted by Horrigan (1966) and Bennell et al. (2006).

S&P's ratings span from C to AAA, but the ratings from CCC to AA may be modified with notches – either a plus or a minus. As a result, there are nine different credit ratings without accounting for notches and 21 different credit ratings if one classifies notched ratings separately. Notches are assigned to credit ratings to show the relative standing within the major rating categories[15]. In order to use credit ratings as the dependent

[14] The inspiration for this approach stems from Jankensgård (2014). Even though refineries are theoretically in the midstream segment, there are several integrated oil companies that are classified under 2911. Included companies in 2911 that do not have E&P operations are excluded in the screening process.

[15] https://www.globalcreditportal.com/ratingsdirect/renderArticle.do?articleId=1019442&SctArtId=147045&from=CM&nsl_code=LIME

variable, a transformation from letters to numbers is necessary. There are clearly differences between a BB+ and a BB- rating, so a transformation to nine different values will certainly eliminate some of the nuances within a general rating class. However, a transformation to 21 different values implies that the effect of being assigned a plus or a minus is of equal importance to being up- or downgraded (provided a company gets downgraded by one notch, for example from B- to CCC+). If the distribution on the three notches within each rating class is equal, the two transformation options will not yield vastly different results. If, however, the vast majority of companies in the BB class are assigned a minus, the nine-value transformation will understate the real difference between the companies in the BB and BBB rating classes.

Previous research has tackled the transformation issue in different ways – Horrigan (1966) and Amato and Furfine (2004) opt for the nine value transformation, while Cantor and Packer (1996) and Bennell et al. (2006) implement the 21 value transformation. Amato and Furfine (2004) argue that a nine value transformation will restrict attention to larger rating changes. Since the large downgrades or upgrades from general rating classes are the main interest of this study, the nine value transformation will be undertaken in the following analyses.

3.1.3 Independent Variables

Selection and Transformation of Ratios

Selecting which financial ratios to include as independent variables can be done in numerous ways, but a general demarcation is whether the ratios are obtained from accounting data or market data. Horrigan (1966) opted for the former while West (1970) chose to use ratios where the majority originated from market data (See Kaplan and Urwitz (1979) for a discussion). The majority of financial ratios included in this study stem from accounting data. Statoil and its associated peer group disclose what can be deemed self-perceived key figures in the first section of their respective annual reports. Accounting standards provide guidelines for the inclusion of some of these ratios, but there is still significant leeway for companies to disclose ratios they believe accurately depict the financial position of the company.

Although several financial ratios are disclosed as “key figures”, not all key figures are financial ratios. These figures are not favourable for comparison across companies, and the only figures used in the following will be ratios. Furthermore, “per share”-ratios need to be modified in order to take into account the varying number of shares issued by each company. If this is not dealt with, companies with a small number of shares outstanding will have inflated “per share” ratios compared to those with a higher number of shares outstanding, even if the numerator in the ratio is equal for the companies. To make “per share” ratios comparable, they are adjusted by the price of each share. Companies with a small amount of shares outstanding will have a significantly higher share price than companies with a large amount of shares outstanding, ceteris paribus. In an efficient market, this effect will exactly cancel out the original per share effect. As a result, Dividend per share, Book Value per share, Earnings per share and Cash Flow per share will be transformed to Dividend Yield, Price/Book, Price/Earnings and Price/Cash Flow in the following.

Adding comparable financial ratios disclosed in Statoil and its associated peer group’s annual reports for 2012 results in 21 ratios relevant for the following analysis. Two ratios are left out due to limited disclosure on the metrics needed to compute the ratios[16]. In addition, the four ratios mentioned explicitly in S&P’s rating criteria are included[17]. Consequently, the final number of variables used is 23. Information on how these financial ratios are calculated is presented in Appendix A.

[16] The two ratios left out are Lease Operating Expenses per Barrel and Debt to Adjusted Capitalization.

[17] These ratios are, as discussed in chapter 2.1.2, FFO/D, Debt/EBITDA, Average Reserve Life Index and Reserve Replacement Ratio.

Table 3.1 Financial Ratios Included in Study

Financial Ratio	Disclosed By Whom
Current Ratio	*Chevron, Eni*
Return on Average Capital Employed (ROACE)	*ENI, Exxon, Lukoil, RDS, Statoil, Total*
Return on Equity (ROE)	*Chevron, Occidental, Total*
Dividend Yield	*Encana, ENI, Lukoil*
Payout Ratio	*Lukoil*
Net Debt Ratio	*BP, Exxon, RDS, Total*
Interest Coverage Ratio	*Chevron*
Total Debt Ratio	*Chevron, ConocoPhillips, Exxon*
Net Debt/Capital Employed	*Statoil*
Debt to Proved Developed Reserves	*Encana*
Cash Flow per BOE	*ENI*
F&D Cost per BOE	*ENI*
Leverage Ratio	*ENI*
Coverage Ratio	*ENI, Exxon, Lukoil*
Profit per BOE	*ENI*
OPEX per BOE	*ENI*
Price/Earnings (P/E)	-
Price/Book (P/B)	-
Price/Cash Flow (P/CF)	-
Funds from Operations/Debt	*S&P*
Debt/EBITDA	*S&P, Encana*
Average Reserve Life Index	*S&P*
Reserve Replacement Ratio	*S&P, Repsol, Statoil*

Note: P/E, P/B and P/CF are adjusted ratios, so none of these are disclosed directly as "key figures". However, they are derived from Earnings per Share, Book Value per Share and Cash Flow per Share, which are disclosed by more or less all companies.

Calculation of Ratios

After determining which financial ratios to include, the next step is to calculate these ratios for every company included in the sample. Datastream offers information on common financial ratios for companies within the sample, but a significant number of ratios consist of input that is not encompassed in the database. This is handled by calculating ratios based on information in the respective companies' annual reports from 2012.

A number of considerations must be taken into account when calculating financial ratios using information disclosed in annual reports. First, companies often use different formulas to calculate the same ratio. Consequently, using values on ratios calculated by the companies themselves will not create values suitable for comparison unless all companies in the sample use the same formulas. In order to answer the research problem asked in this thesis, the key is consistency in formulas used rather than calculating values on each ratio that is coherent with various companies' own calculations. As a result, the same formula is used for all companies within the sample instead of using the values calculated by the companies themselves.

Second, items in companies' financial statements need not include the same elements, which effectively make the case of direct comparison murkier. Fortunately, there are several reporting and disclosure requirements for oil and gas producing activities imposed by FASB (Financial Accounting Standards Board) and SEC (Securities and Exchange Commission), which diminish the majority of problems related to consistency in calculations. This applies especially to F&D costs[18], production and proved reserves calculations. It would prove practically impossible to calculate financial ratios including these inputs without disclosure requirements imposed by FASB and SEC.

Although the disclosures imposed make the process of calculating ratios easier, there is no requirement when it comes to the conversion ratio between oil and gas quantities, which is an influential input for several ratios within the sample. Going by the information in the 2012 annual reports, the companies themselves are split on which conversion ratio that is correct. However, the majority of companies operate with six BCFE (Billion Cubic Feet Equivalent) to one MMBOE (Million Barrels of Oil Equivalents), and this is the factor used in the following. This ratio is based on an energy equivalent conversion method primarily applicable at the burner tip and does not represent a value equivalent at the wellhead[19].

Several E&P companies are headquartered in countries whose currency deviates from the US dollar. Correspondingly, the financial statements in several annual reports are denominated in a foreign currency. This is handled by converting the relevant figures to US dollars using the end-of-year exchange rate.

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[18] Calculated using numbers disclosed in Topic 932 in the companies' annual reports. The final rule was issued at year-end 2008, and it is "intended to provide investors with a more meaningful and comprehensive understanding of oil and gas reserves, which should help investors evaluate the relative value of oil and gas companies". Additionally, companies have to disclose costs related to finding, developing and acquisitions of oil and gas reserves according to the same template, which makes comparison across companies easier. Detailed information on Topic 932 can be found at http://www.fasb.org/cs/BlobServer?blobcol=urldata&blobtable=MungoBlobs&blobkey=id&blobwhere=1175820075990&blobheader=application/pdf

[19] Harvest Operations 2012 Annual Report, p. 1

While F&D costs are straightforward to calculate due to Topic 932 (for information about Topic 932, see footnote 18), operational expenditure (hereby denoted OPEX) is often only disclosed cumulatively. This is not an issue if the company only operates in the E&P segment, but if the company is integrated there is a need to adjust it to only contain E&P-related OPEX. Since the financial ratio disclosed is OPEX per BOE, an integrated company will incur an artificially high value on this ratio[20]. In adjusting for this, we chose to scale OPEX on the share of revenues the company has in the E&P segment compared to total revenues. Pure E&P companies will not be adjusted because the relationship between E&P revenues and total revenues equals one, but integrated oil companies will incur a downward adjustment of their OPEX per BOE. The drawback to this method is that revenues need not be a good proxy to scale OPEX – if the margins are higher in the E&P segment than in the down- and midstream segments, the adjustment will overstate OPEX per BOE for integrated oil companies.

Because inconsistency in calculations poses a major threat to the reliability of results in the following analyses, the imposed requirements on information in the companies' annual reports are strict. Any company that discloses information perceived as inadequate for accurate calculations is left out of the sample. In total, the sample was reduced from 131 to 96 companies during this process.

By eliminating cases with insufficient disclosure of information needed for calculation of financial ratios, one could introduce a bias in the sample if there is a pattern present in the deleted cases. Table 3.2 shows the distribution of ratings for the cases deleted and the cases kept in the sample.

[20] OPEX will increase by increased midstream and downstream activities, but production (the denominator) will not.

Table 3.2 Credit Rating Distributions – Source: S&P

Rating/Omitted?	Cases Left Out	Cases Kept in Sample
CCC	0 %	0 %
B	52 %	34 %
BB	21 %	20 %
BBB	28 %	29 %
A	0 %	9 %
AA	0 %	6 %
AAA	0 %	1 %

While the distribution on the BB and BBB rating classes are similar, there is a deviation on the remaining rating classes. This could represent a potential bias in our sample, but an inclusion with variable scores calculated with lesser data is not desirable. As a result, all cases with missing values on the independent variables will be deleted from the sample.

3.2 Data Screening

In the aftermath of selecting data, there is a need to elaborate upon a number of potential issues that could influence the data set. The majority of these relate to whether underlying assumptions to potential multivariate techniques are violated. While some of these issues may not be relevant to the methodology chosen, a consideration and resolution of these issues before conducting the main analysis are fundamental to an honest analysis of the data (Tabachnick & Fidell, 2013, p. 60).

3.2.1 Missing Values

In addition to the cases deleted due to missing values on independent variables, there are three cases where credit rating information is missing for December 2012: Bonanza Creek Energy Inc, Sanchez Energy Corp. and Warren Resources Inc. These cases are omitted from the sample.

3.2.2 Outliers

An outlier can be described as an observation that deviates so much from other observations as to arouse suspicions that it is generated by a different mechanism (Hawkins 1980) (Acuna

& Rodriguez). Outliers can be found in both univariate and multivariate situations, among both dichotomous and continuous variables and among both independent and dependent variables (Tabachnick & Fidell, 2013, p. 72), and a thorough analysis needs to be conducted to determine whether outliers in a dataset can alter the statistics in a way that gives an inaccurate perception of the overall data.

In the univariate case, an outlier can be observed directly in the raw data. Consequently, screening data for univariate outliers is relatively straightforward. The challenge arises when there are multiple dimensions to a dataset – a case need not be extreme on any of the observable variables, but the combination of values on the n dimensions can deviate substantially from the majority of cases in the sample.

Two of the most common measures to detect multivariate outliers are Euclidean distance (ED) and Mahalanobis distance (MD) (see De Maesschalck et al. (2000) for a discussion). Both of these reflect the distance between a case and the centroid of the remaining cases in the variable space, and a case is a potential outlier if the distance is large. ED does not take correlation between variables into account, and consequently assumes an uncorrelated relationship between the variables. MD gives lower weight to variables with large variances and to groups of highly correlated variables (Tabachnick & Fidell, 2013, p. 74). Because of the correlation typically observed between financial ratios, Mahalanobis distance will be used in the following.

Mathematically, MD can be expressed as:

$$MD_i = \sqrt{(x_i - \bar{x})C_x^{-1}(x_i - \bar{x})^T} \qquad (3.1)$$

Where $\bar{x}$ is the arithmetic mean of all the cases in the data set, and C_x^{-1} is the inverted covariance matrix of the data set.

Two issues arise if one wishes to use MD to detect outliers. First, $\bar{x}$ could be inflated or deflated if there are multiple outliers in the same data set. If a data set contains, say, 10 extreme negative variable scores, the arithmetic mean will be drawn closer to these outliers. As a result, one could choose not to omit a case which is an outlier when the mean is not biased by other outliers.

Second, the inverse covariance matrix is biased when the data set contains several outliers. 10 extreme negative variable scores will inflate the covariance matrix and attract $\overline{x}$, possibly leading to large MDs on positive cases which really are in line with the majority of observations if $\overline{x}$ and C_x^{-1} are not biased by several outliers. Thus, applying MD to the raw data can lead to problems known as masking and swamping – either masking a real outlier or swamping a normal case (Tabachnick & Fidell, 2013, p. 74).

Once an outlier is detected, there are generally three different strategies for reducing its impact: variable transformation, changing the scores on the variables for the outlying cases or deleting outlying cases (Tabachnick & Fidell, 2013, p. 77). Transformation will make the distributions of the 23 variables more normal, which is beneficial in a number of multivariate techniques. However, transformation will decrease the interpretability of the variable scores, and is therefore not considered an option in this thesis. Instead our chosen algorithm consists of a combination of the two latter strategies – score changing and deletion of outlying variables.

If the population is normally-distributed, about one percent of the cases in the sample should be three standard deviations from the mean (Osborne & Overbay, 2004). Accordingly, a deviation from the mean of more than three standard deviations can serve as a rule of thumb when detecting univariate outliers. Since our sample is not normally distributed, this measure cannot serve as a firm rule for detecting univariate outliers. Instead, a case will be classified as an outlier if three or more variable scores are more than three standard deviations from the mean. Even though a case with a univariate outlier need not have a high MD, the probability of the case being a multivariate outlier should be very high when three or more scores are univariate outliers. These cases will be deleted from the sample, since such extreme variable scores are not likely to represent the population in which this thesis is meant to address, namely the E&P industry in general.

In the first round of outlier screening, cases that have outliers on less than three variables will be adjusted using a three-year company average for the variable score in question. A cross-sectional study is merely a snapshot in time and a financial ratio can be severely inflated or deflated due to a wide variety of reasons in one single year. Several cases score normally on the majority of variables, but have one or two extreme variable scores. Instead of omitting these cases, normalization is created by using the three year average for these variable scores. Adjustments are made for all outlying variable scores in the first round of screening and for cases which have two outlying variable scores in the second round of screening. No adjustments are made in the subsequent rounds. While this method clearly can be deemed controversial, the real outliers are not likely to have normalized variable scores that deviate from the original variable score, and they will still be classified as a potential outlier.

After the first screening of outliers, the mean and standard deviation of each variable will change, and other potential outliers could prevail. This is indeed the case in our sample, and the process of outlier detection thus becomes iterative. Hence, the screening process is repeated until there are no more cases that have more than three variable scores that is greater than three standard deviations from the mean. No cases fulfilled this criterion after the fourth round of screening, and the first three rounds saw a total of nine cases being deleted from the sample. The results are given in Table 3.3.

Table 3.3 Results from Univariate Outlier Screening

Company	Round of Elimination	Number of Outlying Variable Scores
Athabasca	1	7
Quicksilver Resources	1	5
Ultra Petroleum	1	4
Inpex	1	3
Halcon	1	3
Forest Oil Corp.	2	6
Imperial Oil Ltd.	2	3
Goodrich Petroleum	3	3
Perpetual Energy Inc.	3	3

Going back to equation 3.1, the estimates for $\overline{x}$ and C_x will now be more robust than the ones obtained by calculating MD for the raw data set. As a result, each case's MD is now likely to be more reliable when it comes to masking and swamping. However, MD remains an imperfect indicator of outliers, and will therefore be used with caution in the following. The criterion for multivariate outliers is Mahalanobis distance at $p > 0.001$, and is evaluated as $\chi^2$with degrees of freedom equal to the number of variables (Tabachnick & Fidell, 2013, p. 74). In our case, any case that has a MD above 49.728 is an indicated multivariate outlier. Cases above the cutoff value are listed in Table 3.4.

Table 3.4 Companies Above Critical MD Value

Company	Mahalanobis Distance
Repsol S.A.	*49.88*
PetroQuest Energy Inc.	*50.62*
Harvest Operations Corp.	*51.74*
Penn Virginia Corp.	*54.80*
Magnum Hunter Resources Corp.	*55.35*
ExxonMobil Corp.	*56.05*
Diamondback Energy Inc	*83.71*
Memorial Production Partners LP	*83.95*

Two cases clearly stand out from the rest of the sample – Memorial Production Partners LP and Diamondback Energy Inc. These two cases have MDs that clearly exceed the defined cutoff value, and are therefore deleted from the sample. The remaining cases are close to the cutoff value, and will not be dropped from the following analyses.

3.2.3 Normality and Linearity

Several multivariate techniques rely on an assumption about normality, that is, that a normal distribution will give a good representation of the actual distributions within the sample. If variables are not normally distributed, the solution is degraded for techniques that rely on this assumption. This is particularly the case when the variables are nonnormal in very different ways (Tabachnick & Fidell, 2013, p. 79).

In assessing whether the assumption about normality holds for a given data set, there are three common procedures to undertake: graphical methods, numerical methods and formal normality tests (see Razali and Wah (2011) for a discussion). Graphical methods are usually very subjective, and we will thus only use numerical methods and normality tests to assess whether the normality assumption holds.

Two central components used when assessing normality through numerical methods are skewness and kurtosis. A skewed variable's mean is not in the center of the distribution (Tabachnick & Fidell, 2013, p. 79), and a distribution that incurs skewness is therefore not symmetrical. Kurtosis relates to the tailedness and the peakedness of a distribution, and effectively represents a movement of mass that does not affect the variance of the variable (DeCarlo, 1997). A variable that displays positive kurtosis will be more peaked than a variable that is normally distributed. Additionally, the tails will be heavier (DeCarlo, 1997).

A variable that is completely normally distributed has values of skewness and kurtosis of zero. Consequently, significant skewness and/or kurtosis indicate a deviation from normality.

Both skewness and kurtosis can be incorporated in a significance test to determine whether the assumption of normality is breached. Essentially, this is done by using a hypothesis test where H_0 states that the variable is normally distributed. The obtained skewness and kurtosis are then compared to the null hypothesis using a z-distribution:

$$Z_{Skewness} = \frac{S - 0}{SE_S} \tag{3.2}$$

$$Z_{Kurtosis} = \frac{K - 0}{SE_K} \tag{3.3}$$

Where S, SE_S, K and SE_K are the observed value and standard error for skewness and kurtosis respectively. If Z exceeds the critical value that corresponds to a predetermined alpha level (we will use $\alpha = 0.01$), the null hypothesis is rejected, and the assumption of normality is not statistically significant for the variable in question.

In addition to numerical methods, the assessment of normality is strengthened when they are used in conjunction with formal normality tests (DeCarlo, 1997). Razali and Wah (2011) use Monte Carlo simulation to compare the power of four of the most common formal normality tests[21], and conclude that the Shapiro-Wilk test is the most powerful. The null hypothesis for this test states that the population the sample is drawn from is normally distributed. If the test's p-value is below the predetermined significance level, H_0 is rejected and the distributions within the sample breach the normality assumption. Table 3.5 shows values for both the numerical tests and the formal normality test:

[21] The four tests included were Shapiro-Wilk, Kolmogorov-Smirnov, Lilliefors and Anderson-Darling.

Table 3.5 Kurtosis Ratio, Skewness Ratio and Shapiro-Wilk Test

	Shapiro-Wilk			Skewness Ratio	Kurtosis Ratio
	Statistic	df	Sig.		
Current Ratio	0.951	82	0.003	2.933	1.850
ROACE	0.911	82	0.000	(5.223)	9.530
ROE Percent	0.797	82	0.000	(9.154)	17.891
DIVIDEND YIELD	0.814	82	0.000	4.818	2.276
PAYOUT RATIO	0.519	82	0.000	(14.726)	55.808
NET DEBT RATIO	0.982	82	0.322	(1.194)	0.436
Interest Coverage Ratio	0.533	82	0.000	15.885	41.065
Total Debt Ratio	0.968	82	0.043	(1.275)	(1.059)
Net Debt/Capital Employed	0.984	82	0.405	(0.907	(0.455)
Debt/EBITDA	0.691	82	0.000	(10.429)	28.309
Reserves Replacement Ratio	0.896	82	0.000	4.538	5.001
Debt to Proved Developed Reserves	0.950	82	0.003	3.077	1.363
Cash Flow per BOE	0.945	82	0.002	3.811	0.085
F&D cost per BOE	0.815	82	0.000	(0.448)	11.140
Leverage Ratio	0.888	82	0.000	4.737	2.476
Coverage Ratio	0.544	82	0.000	14.263	32.264
Profit per BOE	0.921	82	0.000	(0.697)	5.067
OPEX per BOE	0.988	82	0.631	0.754	0.077
Average Reserve Life Index	0.957	82	0.008	2.602	0.641
P/E	0.514	82	0.000	13.554	26.719
P/B	0.917	82	0.000	3.914	1.283
P/CASH FLOW RATIO	0.855	82	0.000	1.421	11.582
FFO/D	0.682	82	0.000	11.615	23.106

The majority of variables display both a p-value that is below our predetermined significance level and Z-values that exceed the critical value (2.58)[22]. Consequently, the assumption of univariate normality does not hold for the majority of our variables.

Several multivariate methods rely on linear correlation coefficients, and the assumption about linearity must therefore be considered in the data screening process. Linearity is present when there is a straight-line relationship between all pairs of variables included in a sample (Tabachnick & Fidell, 2013, p. 83). Appendix B shows a scatterplot

[22] Assume a two-tailed test.

matrix of the independent variables included in the sample. As expected when it comes to financial ratios, several bivariate relationships appear to breach the linearity assumption. To illustrate this, we will elaborate upon the relationship between net debt ratio and return on equity (ROE): If a company incurs more debt, there will be more capital available for investment. Assuming that the company has investment opportunities with positive NPVs, the company's net income will increase. The amount of equity remains constant and ROE will therefore tend to increase if a company's capital structure consists of more debt. However, assuming the most profitable investment opportunities get undertaken first, ROE will grow degressively as a company incurs more debt. Furthermore, costs related to debt overhang, the asset substitution problem and potential bankruptcy costs can result in a significant fall in ROE as a company gets too indebted. This is indeed observable from Appendix B, and goes to show that there are too many factors in play to obtain a relationship among all financial ratios that is perfectly linear. However, we do not observe a large presence of curvilinear relationships, which could make the degradation of results severe.

3.2.4 Multicollinearity

All multivariate techniques seek to include independent variables that correlate with the dependent variable. However, if independent variables are highly correlated with each other, multicollinearity is present. Multicollinearity can increase estimates of parameter variance; yield models in which no variable is statistically significant even though R^2 is large; produce parameter estimates of the "incorrect sign" and of implausible magnitude; create situations in which small changes in the data produce wide swings in parameter estimates; and, in truly extreme cases, prevent the numerical solution of a model (see O'Brien (2007) for a discussion).

Since 23 financial ratios are included in the initial model, one of the biggest challenges in the following analyses is related to the presence of multicollinearity. Financial ratios are very often highly correlated, and the reason is that the underlying determinants of financial ratios often affect the entire company. When a large field is discovered by an E&P company, the effect of this discovery will be present in liquidity, profitability, robustness and growth ratios in the coming years. Financial ratios for that company will therefore tend to be correlated, and this is indeed the case when looking at Table 3.6.

Table 3.6 Collinearity Statistics

Coefficients[a]		
Model	Statistics	
	Tolerance	VIF
PAYOUT RATIO	0.633	1.580
NET DEBT RATIO	0.018	56.150
Current Ratio USD	0.338	2.960
ROACE	0.035	28.728
ROE Percent	0.038	26.168
DIVIDEND YIELD	0.688	1.453
Interest Coverage Ratio	0.019	51.577
Total Debt Ratio	0.117	8.544
Net Debt/Capital Employed	0.023	44.281
Debt/EBITDA	0.730	1.370
Reserves Replacement Ratio	0.469	2.133
Debt to Proved Developed Reserves	0.242	4.136
Cash Flow per BOE	0.338	2.956
F&D cost per BOE	0.690	1.449
Leverage Ratio	0.087	11.439
Coverage Ratio	0,020	50.466
Profit per BOE	0.315	3.172
OPEX per BOE	0.461	2.171
Average Reserve Life Index	0.349	2.863
P/E	0.737	1.356
P/B	0.352	2.843
P/CASH FLOW RATIO	0.390	2.565
FFO/D	0.151	6.613
a. Dependent Variable: Ratings		

Where

$$Tolerance = (1 - R_i^2) \qquad (3.4)$$

$$VIF = \frac{1}{(1 - R_i^2)} \qquad (3.5)$$

Where R_i^2 represents the proportion of variance in the ith independent variable that is associated with the other independent variables in the model (O'Brien, 2007). If tolerance is close to one, the variance in the independent variable in question is not shared with the other independent variables in the dataset. A large tolerance is equivalent to a low Variance

Inflation Factor (hereby denoted VIF) – a VIF value of one means that the independent variable in question is orthogonal to the other independent variables. Although some variables display an acceptable VIF value, multicollinearity is clearly present among several independent variables.

3.2.5 Data Screening summary

The last subchapters have attempted to elaborate upon a number of assumptions that is present for several multivariate methods, and the results are summarized in Table 3.7.

Table 3.7 Data Screening Summary

Assumption	Assessments
Outliers	*Several outliers are removed after a thorough analysis designed to improve the robustness of the forthcoming statistical results.*
Normality	*Although some variables display normality, both numerical and formal normality tests show that normality is breached in general.*
Linearity	*Assumption of perfect linearity breached between several variables, but the observed relationships are not curvilinear.*
Multicollinearity	*Present among several variables in the sample.*

It is evident that several assumptions are breached for our sample, and this will reduce the attractiveness of several multivariate techniques for the subsequent analyses.

4. Methodology

This chapter attempts to introduce the statistical tools used to answer the research problem discussed in chapter 1. A relatively profound review of methodological choices, a discussion of critical assumptions and an evaluation of the overall methodology's robustness will hopefully provide the reader with necessary information to assess, and, if desired, replicate the forthcoming results.

4.1 Principal Component Analysis

4.1.1 Underlying Logic Behind PCA

Our data set contains a vast amount of information about the financial state of public companies within the E&P industry in 2012. Some of this information could either be redundant for the purposes of this analysis or accounted for multiple times. For this thesis, an optimal methodology needs to take both of these aspects into consideration, and a Principal Component Analysis could serve as a viable first step to do just that.

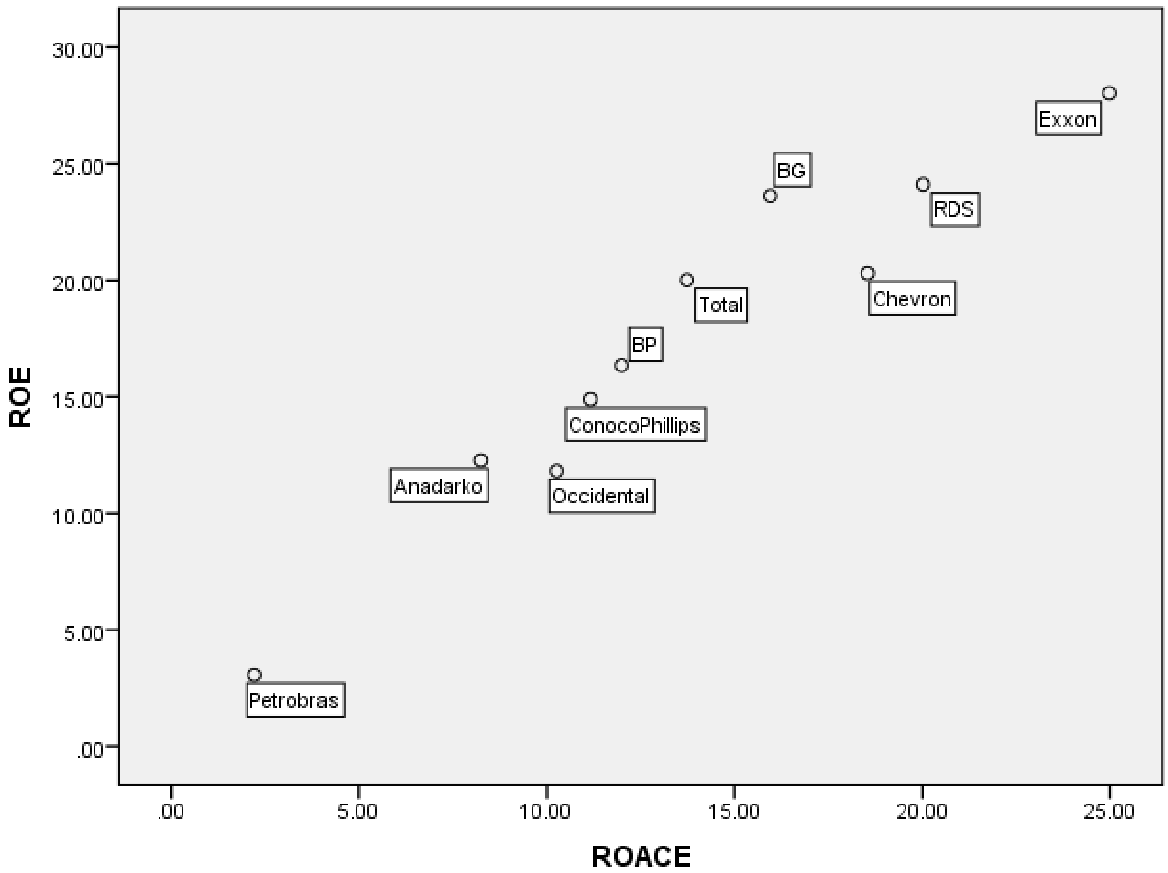
Principal Component Analysis (hereby denoted PCA) was first introduced by Pearson in 1901, and the central idea is to reduce the dimensionality of a data set in which there are a large number of interrelated variables, while retaining as much as possible of the variation present in the data set (Jolliffe, 1986, p. 1). A typical situation in which use of PCA is advantageous is when the researcher deals with detailed survey data. There are typically several questions asked to the interviewee where the intention is to highlight nuances related to a larger topic. If, say, five questions are needed to create a holistic impression of that topic, the answers to these questions are likely to be highly correlated because the underlying topic is equal among those five questions. If all questions were to be included as independent variables in a regression analysis the researcher will incur severe multicollinearity issues. The logic behind PCA is that a linear transformation of these five questions will result in a number of orthogonal underlying dimensions, principal components, that is lower than the number of initial variables (questions) *as long as these variables are intercorrelated in the first place.* A linear transformation procedure will create as many principal components as initial variables. However, some of these components will, if intercorrelation is present, account for a substantially lower share of variance within the data set than others. As a result, these components can be deleted without losing much of the variation, thereby reducing the dimensionality of the data set.

A data set that consists of 23 financial ratios will, because the underlying *topic* is a company, tend to incur the same problems with multicollinearity. In other words, several of the data set's existing 23 dimensions can likely be deleted without loss of much information. PCA seeks to extract the underlying structure of the data set, and among intercorrelated variables, this structure can be depicted in a less complicated way than what the original data set implies.

4.1.2 Illustration of PCA

In an attempt to clarify exactly how PCA works, a simple two dimensional example is considered in the following section. Figure 4.1 shows the values on two of the most common profitability ratios, ROACE and ROE, among selected companies within Statoil's peer group.

Figure 4.1 Return Measures of Selected E&P Companies 2012 – Source:Datastream



Unsurprisingly, the chart displays a substantial correlation between the two ratios. If both of these are included in a regression analysis, the multicollinearity issues discussed in section 3.2 are likely to occur. In situations like these, the use of PCA often improves regression results.

A PCA creates a linear transformation of initial variables that retain more in-sample variance than any other linear combination when the dimensionality of the data set is reduced. Computation of the principal components reduces to the solution of an eigenvalue-eigenvector problem for a positive-semidefinite symmetric matrix (Jolliffe, 1986, p. 1). In this example, the optimal linear transformation when it comes to retaining variance in ROACE and ROE is done by using eigenvalues and the corresponding eigenvectors of a covariance matrix for ROACE and ROE[23]. Provided that ROACE and ROE do not correlate perfectly, singularity is not present and the covariance matrix can be diagonalized. Since this entails that all values in the matrix except the main diagonal will be zero, the two principal components will be uncorrelated.

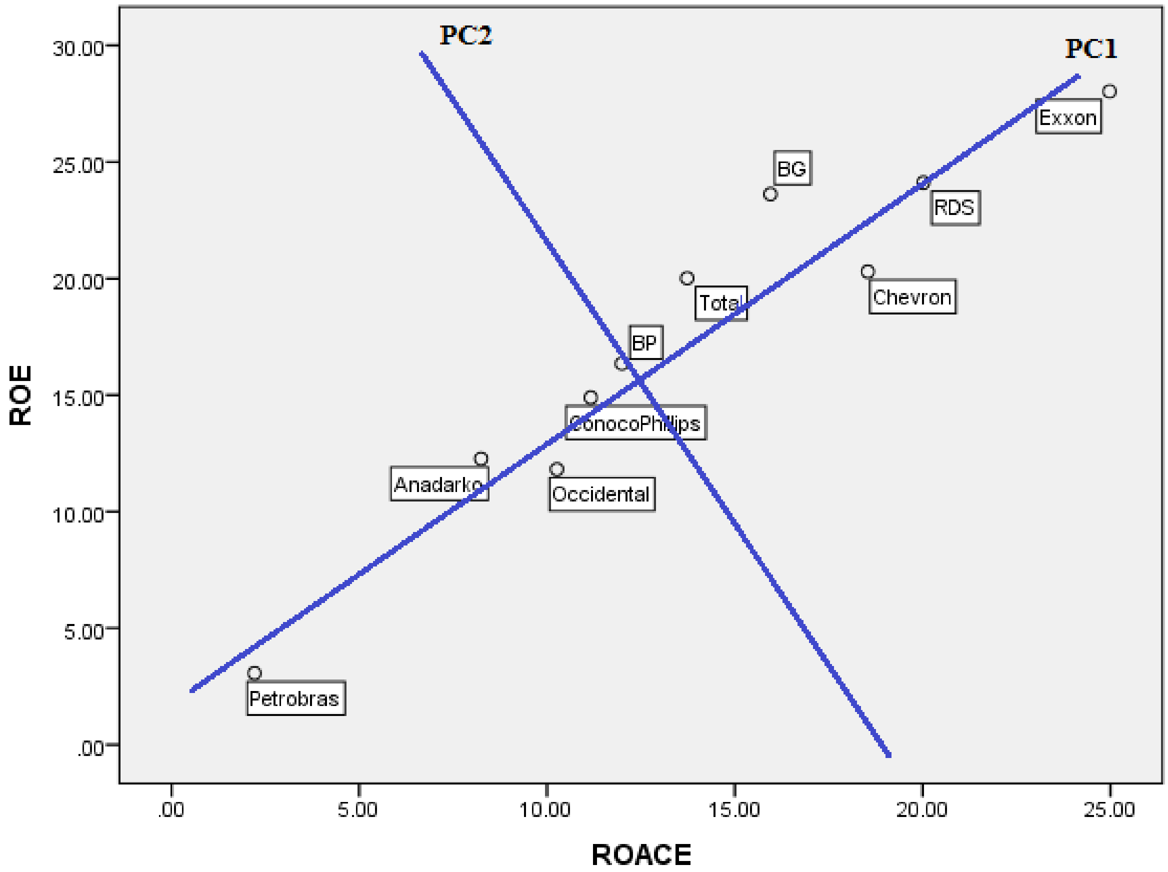
Diagonalization of the correlation matrix is done by pre- and post-multiplying it with a matrix whose columns consists of eigenvectors corresponding to the covariance matrix's eigenvalues (Tabachnick & Fidell, 2013, p. 622). The result is a matrix whose eigenvalues will be located along the main diagonal. The remaining numbers in the matrix will be zero, since the principal components are by definition uncorrelated.

Conducting a PCA for ROACE and ROE yields eigenvalues of 1.961 and 0.039. Consequently, the first principal component explains 98.05 percent of the total variation in ROACE and ROE[24]. This result shows that as long as the variables in question are correlated, the dimensionality in the original data set is often excessive, and a dimensionality reduction is possible without losing much of the variance. The process becomes more intuitive when illustrated graphically:

[23] How to calculate eigenvalues and eigenvectors for a 2X2 matrix is shown in Appendix D.

[24] $\frac{1.961}{1.961+0.039} = 0.9805$ Results from the PCA is given in Appendix C

Figure 4.2 Two-dimensional PCA illustration – Source: Datastream



In our example, almost all variation in ROACE and ROE can be explained by only one dimension – the first principal component. PC2 becomes redundant because it only accounts for 1.95 percent of the variation in the initial data set. If the *initial* variables are uncorrelated, however, PCA will yield eigenvalues of one and no principal component can account for more variance than either of the initial variables.

4.1.3 Assumptions

Although the assumptions of PCA are not as stringent as those of multiple regression, there are still some issues that need to be considered to determine whether a PCA is appropriate for a given data set. First of all, multicollinearity needs to be present. However, singularity cannot.

PCA utilizes correlation or covariance matrices. These correlations are by definition linear, and a data set whose independent variable relationships are non-linear will not be detected by such a matrix. As a consequence, PCA becomes less powerful when the assumption about linearity is violated.

A covariance matrix is often more reliable when the sample is large, and a small sample can thus result in a degraded PCA (Tabachnick & Fidell, 2013, p. 618). This is especially the case when the communalities are low[25]. Hence, large average communality loosens the restrictions on sample size.

Outliers can alter a covariance matrix substantially, and the results of the PCA are therefore sensitive to the presence of outliers. If no outliers are present the covariance matrix will be more reliable, effectively yielding principle components that more accurately describes the underlying structure of the data set.

4.1.4 How PCA will be used

In isolation, a PCA does not yield results that go beyond that of reducing the dimensionality of a data set. Consequently using PCA alone will not suffice when it comes to answering the research problem of this thesis. Rather, the results from the PCA serve as an introductory analysis that is used to make sure the main regression analysis is conducted in a robust way.

When PCA is used as an introductory analysis for a subsequent regression, the original independent variables are often substituted with the principal components that typically have an eigenvalue above one. A procedure like this will ensure that all independent variables used in the regression are orthogonal, but if the original independent variables are of interest, a regression on PCs may not be appropriate. This is indeed the case for our research problem – a transformation of independent variables will not answer which financial ratios best describe the variation in S&P's credit ratings. Instead, we would find out which principal components best described the variation. Such an analysis is not relevant to our research problem, and we will instead use PCA merely as a reference frame for selecting independent variables. This is beneficial because variables that load highly on PCs with large eigenvalues tend to be correlated. Including several variables with a high loading on the same PC in a regression will create issues with multicollinearity, and this is to a large extent

[25] If a communality of a variable is high, it means that the principal components account for a large share of the variation in the original variable.

prevented by conducting an introductory analysis like a PCA. Exactly how the variable selection is conducted is elaborated upon in section 4.1.6.

4.1.5 Rotation of Principal Components

Principal components are linear transformations of every variable in the original data set. This may result in principal components that contain a high factor loading for multiple initial variables. If several variables load highly, the interpretability of the PC is often more dubious.

One way to simplify the interpretation of PCs is by rotation. In general, there are two main rotation categories: orthogonal and oblique rotation. The former performs rotation with the assumption that the principal components are uncorrelated, while the latter allows for correlation between the principal components. Since our main goal with the PCA is to obtain variables that minimize multicollinearity, we opt for an orthogonal rotation. In varimax rotation, which is arguably the most common orthogonal rotation procedure, the sum of the variances of the squared loadings within each column of the loading matrix is maximized (Dunteman, 1989, p. 49). Essentially, this procedure makes high initial loadings higher and low initial loadings lower by using a transformation matrix (Tabachnick & Fidell, 2013, p. 625).

4.1.6 Variable Selection

One of the main challenges with using PCA as an introductory analysis for a subsequent regression analysis is that these two multivariate techniques aspire to reach two different goals: PCA seeks to retain components that account for as much variation *within the data set* as possible, and a regression analysis seeks to retain independent variables (or principal components) that account for as much as possible of the variation in the dependent variable. Even if a component explains a substantial part of the variation within a data set, it need not be correlated with the dependent variable. In this case the component is important in the PCA-perspective, but only creates noise in the subsequent regression analysis.

Various variable selection techniques have been proposed in the literature, and the differences between them often relate to how they treat the trade-off between external considerations (correlation with the dependent variable) and internal relationships (correlation between the independent variables) (Jolliffe, 1986, pp. 107-110).

Jolliffe focuses on finding a selection technique that preserves as much of the variation in the initial data set as possible. Various techniques are suggested:

- Find the n variables that have the highest loading on the n PCs which is lower than the cut-off eigenvalue, and delete these variables. The reasoning behind this method is that small eigenvalues corresponds to near-constant relationships between a subset of variables. If one of the variables involved in such a relationship is deleted, then little information is lost (Jolliffe, 1986, p. 108).
- Find the variables that load most on the n principal components that have eigenvalues larger than the cut-off eigenvalue, and delete all other variables.

Mansfield et al. (1977) incorporate a technique that first deletes the PCs with smallest eigenvalues, and then use an algorithm that deletes variables that result in the minimum increase in residual sum of squares. Daling and Tamura (1970) delete the last few PCs, and then use varimax to rotate the remaining PCs (Jolliffe, 2002, p. 188). Furthermore, they select a variable that have a significant correlation with the dependent variable for each of the remaining PCs.

We will use several variable selection strategies in an attempt to find the combination of financial ratios that best fits the relevant considerations of this research problem. Some of these will replicate previously suggested selection techniques, and others will deviate slightly from the work that has been done before. All strategies pursued are presented in Table 4.1, and will be discussed further in section 5.1.2.

Table 4.1 Summary Variable Selection Strategies

Strategy	Description	Introduced by
Case 1	*Select Values with largest loading on each Principal Component without checking for dependent variable correlation.*	*Jolliffe*
Case 2	*Select values with largest loading on each Principal Component subject to dependent variable correlation. The weighting between internal and external considerations is 50/50.*	-
Case 3	*Only use PC's that have a significant correlation with Y, and then use the variable that has the highest loading on each component selected.*	*Daling and Tamura*
Case 4	*Only use variables that correlate significantly ($p<0.05$) with Y. Take the highest loading on each component.*	-

The purpose of this thesis does not directly relate to the goal of preserving as much variation within the financial ratios included as possible. Rather the PCA is a tool to mitigate the presence of multicollinearity. If all 23 financial ratios are included, the explanatory power of the overall model will be higher than for any subsection of financial ratios. As a result, the external considerations will benefit from the inclusion of more variables. However, since multicollinearity will be present in a model like this, internal relationships need to be taken into account as well. Consequently, these two considerations represent a trade-off which will be tackled by evaluating each of the four variable selection strategies against both the overall goodness of fit and the statistical significance of each financial ratio included. We expect that models with a large number of retained financial ratios incur multicollinearity to a larger degree than models with a small number of ratios. This is likely to result in inflated parameter variances (O'Brien, 2007) which will limit the ability to make statistical inferences. As a result, the preferred model will be the one which expresses a satisfactory goodness of fit as well as including financial ratios that show a statistically significant relationship with the dependent variable.

4.2 Multinomial Logistic Regression

4.2.1 Underlying Logic Behind Multinomial Logistic Regression

Multinomial logistic regression deviates from multiple regression in several ways, and one of the most important differences is that the former treats different values on the dependent variable as groups. The optimization procedure is conducted with regards to estimating the probability of a case to have a particular value on the dependent variable, or equivalently, belonging to the group corresponding to that value. In our analysis, the multinomial logit model evaluates the probability that a given E&P company belongs to a rating class given that company's pattern of values on the included financial ratios in the model.

A model that predicts probabilities of belonging to a particular group will have to include more than one equation if there are more than two values on the dependent variable (Menard, 1995, pp. 12-14). The multinomial logit model uses one category on the dependent variable as the reference group, and then compares the probability of belonging to this group with the probability of belonging to the other groups. Consequently, there are as many equations in the model as there are categories on the dependent variable, excluding the reference category. The estimated parameters in each regression equation are calculated relative to the reference group (Amdouni & Soumare, WP). Using Menard's notation, we can write the odds ratio for a given group as:

$$g_h(X_1, X_2, \dots, X_n) = e^{a_h + b_{h1}X_1 + b_{h2}X_2 + \cdots + b_{hn}X_n} \quad (4.1)$$

$$h = 1,2, \dots, M-1$$

where n represents the independent variables and h is the categories on the dependent variable (Menard, 1995, p. 13). The odds ratio is essentially the ratio of the probability that a case belong to a particular group to the probability of the case belonging to all other groups.

The probability that Y belongs to a particular group h is:

$$P(Y = h | X_1, X_2, \dots, X_n) = \frac{e^{a_h + b_{h1}X_1 + b_{h2}X_2 + \cdots + b_{hn}X_n}}{1 + \sum_{h=1}^{M-1} e^{a_h + b_{h1}X_1 + b_{h2}X_2 + \cdots + b_{hn}X_n}} \quad (4.2)$$

Since the reference category is referred to as $h = 0$, the numerator of the expression for that category equals one. It is observable from equation 4.2 that the probability of belonging to a particular group will always be between zero and one.

4.2.2 Maximum Likelihood Estimation

It prevails from equation 4.1 that the equations used in the multinomial logit model are not linear, and this does not comply with the OLS estimation of coefficients. Instead, the optimization procedure in multinomial logistic regression involves estimation of coefficients according to a maximum likelihood criterion. The goal with such a procedure is to find the best linear combination of predictors to maximize the likelihood of obtaining the actual outcome frequencies (Tabachnick & Fidell, 2013, p. 441). A log-likelihood function is maximized to obtain this combination, and this function essentially takes the values of the independent variables included and the corresponding coefficients into account in indicating how likely it is to obtain the observed frequencies of the dependent variable (Menard, 1995, p. 13). Initially, these coefficients are determined arbitrarily, and the residuals of the model are then analyzed to see whether the coefficients have other values that would ensure that the predicted frequencies coincide with the actual frequencies to a larger extent. This iterative procedure continues until convergence is reached, that is, when an analysis of the residuals result in a change in coefficients that is negligible.

4.2.3 Assumptions

One reason why logistic regression is widely used is that the obtained results do not hinge upon a significant amount of assumptions, as is often the case for other multivariate techniques. There are, for instance, no assumptions about multivariate normality, linearity between the initial variables and homoscedasticity (Tabachnick & Fidell, 2013, p. 439), but some assumptions nevertheless need to be addressed:

- Linearity is assumed between the independent variables and the transformed dependent variable (the logit)
- Absence of multicollinearity
- The dependent variable has to be either nominal or ordinal

These assumptions, along with the limitations of our data set discussed in the previous chapter, will be assessed in section 4.3. The exception is the assumption about the linearity in the logit – the optimal combination of financial ratios is not yet known, and we cannot test this assumption until this is the case.

4.2.4 How Multinomial Logistic Regression Will be Used

Multinomial logistic regression can be used both as a tool to explain which determinants are central to a dependent variable, and as a tool for prediction (Amdouni & Soumare, WP). The main research problem in this thesis is coherent with the first aspect – finding which financial ratios are the most central determinants when it comes to explaining the variation in credit ratings. As a result, the multinomial logit model will be used primarily for this purpose and not so much for prediction.

Logistic regression has two types of inferential tests: tests of models and tests of individual predictors (Tabachnick & Fidell, 2013, p. 459). A number of measures can be used to evaluate a multinomial logit model, and a brief elaboration on the measures included in our analysis is presented here. Additionally a measure that assesses the overall goodness of fit - the Nagelkerke Pseudo R^2- is presented.

- *Likelihood Ratio Test of Full Model:* If all financial ratios included in a model are unrelated to observed credit ratings, the inclusion of these ratios will not contribute to a more accurate prediction. A first step to test if this is the case is by checking whether the financial ratios included together improve the predictive power of the model. If the difference in predictive power of a Constant-only model and our full model is not statistically significant, we cannot conclude that there is a relationship between the independent variables and the dependent variable that cannot be attributed to chance (Menard, 1995, p. 18).
- *Likelihood Ratio Tests of Individual Variables:* Even if a model contributes statistically to prediction, there may be independent variables included in the model that do not. The individual likelihood ratio test investigates if there is a statistically significant improvement in the model if a certain independent variable is included.
- *Odds Ratio:* An odds ratio is defined as the exponent of a coefficient included in a logistic regression equation, and describes the percentage change in odds of belonging to a comparison group compared to the reference group when the predictor in question increases by one unit.
- *Nagelkerke Pseudo R^2:* A multivariate technique that uses OLS as an optimization procedure evaluates a model by R^2- that is, how much of the variance in the dependent variable that can be explained by the included independent variables. In a multinomial logistic regression model no measure with such an interpretation exists, but there are several approximations. Even though this measure has no intuitive interpretation, it gives an indication of the goodness of fit.

4.3 Evaluating the Methodology With Regards to Assumptions

The main conclusion of the data screening process in chapter 3 is that several assumptions associated with common multivariate techniques are breached. Outliers, non-normality, non-linearity and multicollinearity are all present in the initial data set. If the analysis is going to yield robust results, there is a need for a methodology that does not depend critically on the violation of these assumptions.

The screening process revealed both univariate and multivariate outliers in our data set. Deletion of these cases will ensure a more stable correlation matrix, which is critical for the outcome of a PCA. As a result the initial presence of outliers is, after the analyses presented in chapter 4.2, not perceived to alter the robustness of the chosen methodology.

Normality is not required in neither PCA nor multinomial logistic regression (Tabachnick & Fidell, 2013, pp. 443,618). A traditional multiple regression assumes normality, and if such a multivariate method was to be used, the robustness of the analyses is likely to worsen compared to the multinomial logit model.

Because the correlation matrix is by definition linear, the results of the PCA are weakened by non-linearity. However, multinomial logistic regression does not require linearity among the original variables. Since PCA is only used as an introductory analysis, we believe that the methodology does not suffer severely from the non-linearity present in the data set.

Multicollinearity issues are substantial in the original data set, and this is tackled by using PCA. Even though the use of initial variables (instead of principal components) will entail some multicollinearity, the PCA ensures that it is kept at a minimum. Regarding the multinomial logistic regression, none of the assumptions that can be tested prior to the analyses are violated. The assumption about linearity in the logit needs to be evaluated when the optimal independent variables are known. To conclude, the data set's characteristics is likely to degrade the results of several common multivariate techniques, but neither of these characteristics appear to violate assumptions associated with the two techniques we choose to use in the methodology. As a result, the data set's characteristics do not appear to pose a significant threat to the robustness of the forthcoming analyses.

4.4 Out-of-Sample Testing

The model culminating from our chosen methodology displays output that shows how well the model fits the sample used in the study. If the sample does not give an entirely accurate representation of the underlying population, the model optimization could overfit the model to the sample. This yields a better model fit for the original sample, but it can degrade the applicability of the model to other samples. To assess whether this is the case, an out-of-sample test is conducted by using credit ratings and financial ratios for the same E&P companies from year-end 2011. By testing the model on observations that are not used in the model optimization we can evaluate the usefulness of the model outside the sample. This is especially important in cross sectional studies where the sample is relatively small.

5. Analysis and Findings

In this chapter, the results from our hypothesis testing are presented. Section 5.1 elaborates on the PCA, while section 5.2 presents both how the optimal combination of financial ratios was selected, a description of the ratios included in this combination and an in-depth interpretation of our final model.

5.1 Introductory Analysis

5.1.1 Requirements

The discussion in chapter 4.3 concludes that our data set does not severely violate the underlying assumptions of PCA. Even if assumptions are not violated, we still need to assess the structure of the correlation matrix as a whole to see if a PCA has the potential of yielding adequate results. Two common formal tests offered in most statistical packages are presented: Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity.

KMO culminates in a value between zero and one, and indicates how much of the variance displayed in the data set that might come from underlying factors. According to Dziuban & Shirkey (1974), the KMO measure tends to increase when the number of variables increases, the number of factors decreases, correlation increases and when the number of cases increases. If KMO is lower than 0.5, a PCA is not useful (see Parinet et al. (2004) for a discussion).

Bartlett's test of sphericity investigates the usefulness of a PCA by testing whether the data set's correlation matrix is an identity matrix. In an identity matrix all other values other than the main diagonal are zero, which occurs when all independent variables are uncorrelated. If this is the case PCA will be of no use, because all principal components will have an eigenvalue of one. Rejection of Bartlett's test of sphericity is an indication that the data set is appropriate for a PCA (Dziuban & Shirkey, 1974), and this occurs when the significance level of the test is below a predetermined alpha value.

Results from these two tests are presented in Appendix E. Since the KMO measure is 0.683 and Bartlett's test of sphericity is significant at the 0.01 level, we can safely proceed with the PCA.

5.1.2 Principal Component Analysis

After running our post-screened data set through a PCA, we obtain a rotated component matrix that shows how different financial ratios load on each principal component. The matrix is presented in Table 5.1.

Table 5.1 Rotated Component Matrix

	1	2	3	4	5	6	7	8	9
Current Ratio USD				.702					-.323
ROACE				.795					
ROE Percent				.788					
DIVIDEND YIELD			-.459			.415	.423		
PAYOUT RATIO							-.819		
NET DEBT RATIO	.913								
Interest Coverage Ratio		.912							
Total Debt Ratio	.865								
Net Debt/Capital Employed	.878								
Debt/EBITDA									.860
Reserves Replacement Ratio					.787				
Debt to Proved Developed Reserves	.747					.398			
Cash Flow per BOE			.863						
F&D cost per BOE								.754	
Leverage Ratio	.913								
Coverage Ratio	-.302	.913							
Profit per BOE			.845						
OPEX per BOE						.856			
Average Reserve Life Index					.894				
P/E								.735	
P/B	.301		.414			-.534			-.326
P/CASH FLOW RATIO					.512		.486		
FFO/D	-.454	.821							

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

Nine PCs have eigenvalues above one, and these are presented in the rotated component matrix[26]. To make the matrix orderly, variables that have a correlation with the retained PCs lower than 0.3 in absolute value are not shown. These variables do not load highly on the PCs that explain most of the variation within the sample, and are therefore not as interesting for our purposes as the variables that load highly. Between them these nine PCs account for just over 83 percent of the variation within the sample (see Appendix F).

All financial ratios that load highly on the first PC are debt ratios. Since variables that load highly on the same PC typically are correlated, it is in line with expectations that debt ratios will load on the same component. What is nevertheless interesting is that debt ratios appear to be more influential than other types of ratios with regards to explaining in-sample variation. Two variables have the highest loading on this PC – Net Debt Ratio and Leverage Ratio.

Furthermore, we observe that coverage ratios – typically ratios that indicate the ability to pay costs associated with debt by internally generated funds – load highly on the second PC. Profitability and cash flow ratios denominated in barrels of oil equivalent (BOE) load highest on the third PC. Common profitability measures like ROE and ROACE load highly on the fourth PC. In line with our illustration in chapter 4.1.2, we see that the correlation between ROE and ROACE results in a high loading on the same PC. Petroleum-specific financial ratios such as Reserves Replacement Ratio and Average Reserve Life Index (ARLI) load highly on the fifth component.

As discussed in chapter 4.1.4, the PCA does not in and of itself yield sufficient insight to answer our research problem, but it is used as a tool for mitigating issues with multicollinearity. The consideration with multicollinearity is taken into account through the four different variable selection strategies. Before presenting which financial ratios that are selected for the subsequent multinomial logistic regressions, each variable selection strategy will be explained in detail:

1. The first variable selection strategy pursued replicates one of the strategies proposed by Jolliffe (1986) – For each of the PCs that is retained (in our case: PCs with an

[26] There are multiple approaches when it comes to deciding on the optimal number of retained PCs. We will not delve on this however, since the PCs themselves are not of primary interest with regards to the research problem in this thesis.

eigenvalue above one), select the variable with the highest loading on each PC. Since nine PCs are retained, the regression model will have nine independent variables. This strategy does not take correlation with ratings into account, and we expect to see some of the financial ratios included with this strategy to become noise in the multinomial logit model.

2. The second variable selection strategy has to our knowledge not been proposed in previous research. Essentially this strategy recognizes that both internal and external considerations, that is maintaining variation within the sample and making sure there is correlation between the financial ratios included and credit ratings, need to be taken into account. This is done by assigning an equal weight on both how much a financial ratio loads on a PC and to what extent that financial ratio correlates with the dependent variable. A strategy like this will mitigate the risk of including financial ratios that only introduce noise in the multinomial logit. At the same time, we will maintain financial ratios that are likely to have a relatively high loading on the retained PCs. The score on each financial ratio is calculated by using the following formula:

$$SCORE_n = PC_{Loading} \times p + \rho_{n,y} \times (1 - p) \qquad (5.1)$$

Where $PC_{Loading}$ is each financial ratio's correlation with a retained PC, p is the weight assigned to this consideration and $\rho_{n,y}$ is the correlation coefficient between the financial ratio in question and the dependent variable. The weight p is set to 0.5, so the internal and external considerations are assumed to be of equal importance. Once all scores are calculated, the financial ratios with the highest score on each PC are included in the multinomial logit. Consequently this strategy will include as many financial ratios as there are retained PCs. By introducing a focus on external considerations, we expect this strategy to incur multicollinearity to a higher degree than strategy one.

3. Inspired by (Daling & Tamura, 1970), the third variable selection strategy only includes financial ratios on PCs that correlate significantly at the five percent level with the dependent variable. This means that PCs that do not correlate significantly with Y are not considered, thereby leaving out the financial ratios that correlate highly with these PCs. If two or more financial ratios on the same PC correlate

significantly with Y, the ratio with the highest factor loading is selected. We do not expect all nine PCs to be significantly correlated with Y, so the number of financial ratios included in the multinomial logit is likely to be lower.

4. The last variable selection strategy applies a similar logic as the third strategy, but rather than focusing on the correlation between PCs and Y, it focuses on the correlation between financial ratios and Y. Financial ratios that do not correlate at the five percent significance level with Y are not eligible for inclusion in the subsequent multinomial logit. If there are two or more financial ratios that fulfil this criterion on the same PC, the ratio with the highest factor loading is selected. A strategy like this is to our knowledge not tested in earlier research.

The retained financial ratios for each variable selection strategy are presented in table 5.2:

Table 5.2 Variables Included in Selection Strategies

Variable Selection Strategy	Financial Ratios Included
Strategy 1	*Net Debt Ratio, Coverage Ratio, Cash Flow per BOE, ROACE, ARLI, OPEX per BOE, Payout Ratio, F&D Cost per BOE, Debt/EBITDA*
Strategy 2	*Net Debt Ratio, Coverage Ratio, Cash Flow per BOE, ROACE, Reserves Replacement Ratio, OPEX per BOE, Payout Ratio, Price/Earnings, Debt/EBITDA*
Strategy 3	*Net Debt Ratio, Coverage Ratio, Cash Flow per BOE*
Strategy 4	*Net Debt Ratio, Coverage Ratio, Cash Flow per BOE, ROACE, Reserve Replacement Ratio, Dividend Yield*

Detailed information on the variable selection is presented in Appendix G. Generally, the same ratios prevail in different variable selection strategies. Perhaps the most interesting difference between the strategies is the number of variables retained: The two first strategies retain nine financial ratios, while strategy three and four retain three and six ratios respectively. In order to determine which strategy that creates the best model for our purposes, a multinomial logistic regression needs to be carried out.

5.2 Multinomial Logit Model

5.2.1 Evaluation of Variable Selection Strategies

In accordance with the discussion in section 4.1.6, the Pseudo R^2 and the percentage of included independent variables that are statistically significant is presented in Table 5.3:

Table 5.3 Evaluation of Variable Selection Strategies

Variable Selection Strategy	Pseudo R Squared	Percentage of Variables Significant at the 0.05 level
Strategy 1	*0.848*	*33 %*
Strategy 2	*0.822*	*33 %*
Strategy 3	*0.697*	*100 %*
Strategy 4	*0.816*	*83 %*

As expected the Pseudo R Square generally increases with the number of financial ratios included. The first two strategies include nine financial ratios, and have a higher Pseudo R Square than the two latter strategies which include fewer ratios. Multicollinearity appears to be present in the two first strategies, as only one third of included ratios have a relationship with the dependent variable that cannot be attributed to chance. Even though the overall model in the two first strategies shows a satisfactory goodness of fit, the ability to make statistical inferences is barely present. As a result we conclude that the two first variable selection strategies culminate in models that are not optimal for the research problem in this study.

We are left with two strategies that yield two relatively different models. Regarding goodness of fit, strategy four appears more satisfactory than strategy three. This is not surprising when one takes the number of included financial ratios in the models into account – strategy four culminates in a model that includes twice as many financial ratios as strategy three. Taking the difference in retained financial ratios into account, strategy three appears to have a very good fit. This opinion is strengthened by the fact that all included financial ratios' contribution to the model is statistically significant, whereas this is the case for 83 percent of the independent variables in strategy four.

Overall the two retained models both appear to be quite good and the final model choice will be somewhat subjective. We choose to go with strategy three, as the three financial ratios included in that model appear to explain more of the variation in the dependent variable *on a per ratio basis.* Additionally, the variable selection strategy that was used to obtain this combination of financial ratios builds on previously published work (Daling & Tamura, 1970).

5.2.2 Financial Ratios Included in the Final Model

In order to use the model for statistical inference, it is important to understand what information the included financial ratios actually convey. As a consequence, the three ratios in our chosen model will be elaborated upon briefly before the final model is interpreted.

Net Debt Ratio

In order to create value for shareholders, all E&P companies have to incur CAPEX that need financing. If the cash flow from operations exceeds the funds required to comply with CAPEX plans, an E&P company need not turn to the external debt and equity market to obtain financing. The Net Debt Ratio (hereby denoted NDR) provides information on the extent to which a company's operations are financed by debt, and is calculated using the following formula:

$$Net\ Debt\ Ratio = \frac{Net\ Debt}{Equity + Net\ Debt} \tag{5.2}$$

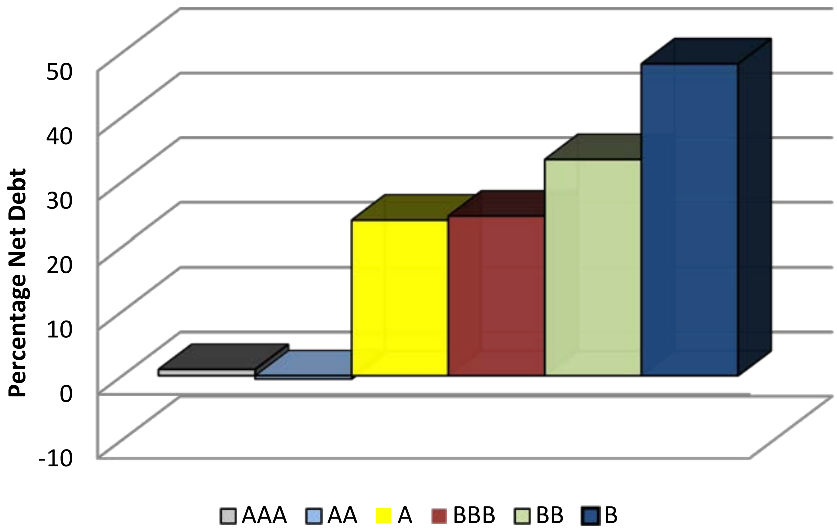
Where

$$Net\ Debt = Total\ Debt - Cash\ and\ Short\ Term\ Investments$$

Several companies within Statoil's peer group disclose the NDR as a key financial figure in their annual reports from 2012[27]. Typically, companies that have less profitable operations need to obtain more financing externally. However, there are benefits and drawbacks to all types of financing and hence the amount of debt carried by a company need not solely depend on its profitability. Figure 5.1 shows each rating class average NDR.

[27] Royal Dutch Shell, Total, Exxon and BP.

Figure 5.1 Average NDR Differentiated on Rating Class – *Source: Datastream*



Coverage Ratio

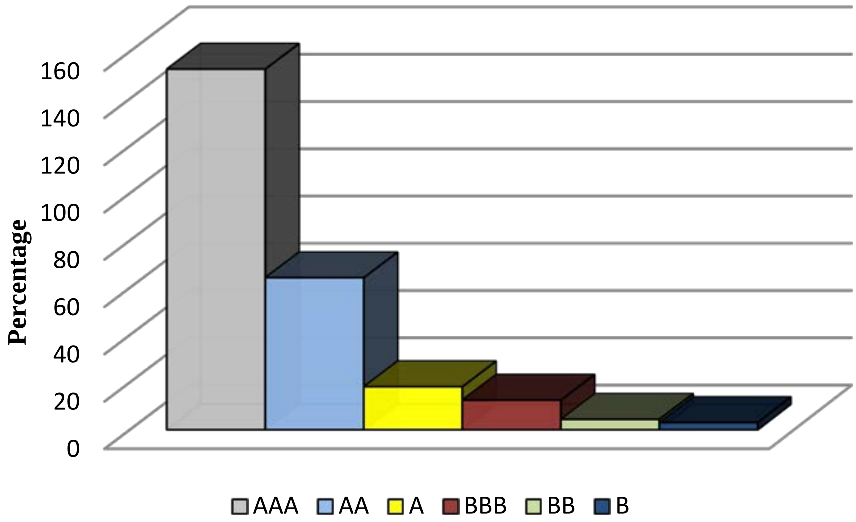
The Coverage Ratio (hereby denoted CR) is labeled a key financial figure in both Eni's and Exxon's annual reports from 2012, and is given by the following formula:

$$Coverage\ Ratio = \frac{Operating\ Profit}{Net\ Finance\ Charges} \tag{5.3}$$

CR serves as a measure for financial discipline[28], and indicates a company's ability to pay the interest expenses on its outstanding debt. A low CR either indicates poor profitability and/or a large debt burden. If a company displays both a low NDR and CR, the operating profit for that company must be relatively low. We expect a negative correlation between NDR and CR, and Figure 5.2 suggests that this is indeed the case.

[28] Eni's 2012 Annual Report, page 106.

Figure 5.2 Average CR Differentiated on Rating Class - Source: Datastream



Cash Flow per BOE

Cash Flow per BOE (hereby denoted CFBOE) is disclosed as a key financial figure in Eni's annual report, and is calculated as:

$$Cash\ Flow\ per\ BOE = \frac{Cash\ Flow\ from\ E\&P\ Activities}{Production} \qquad (5.4)$$

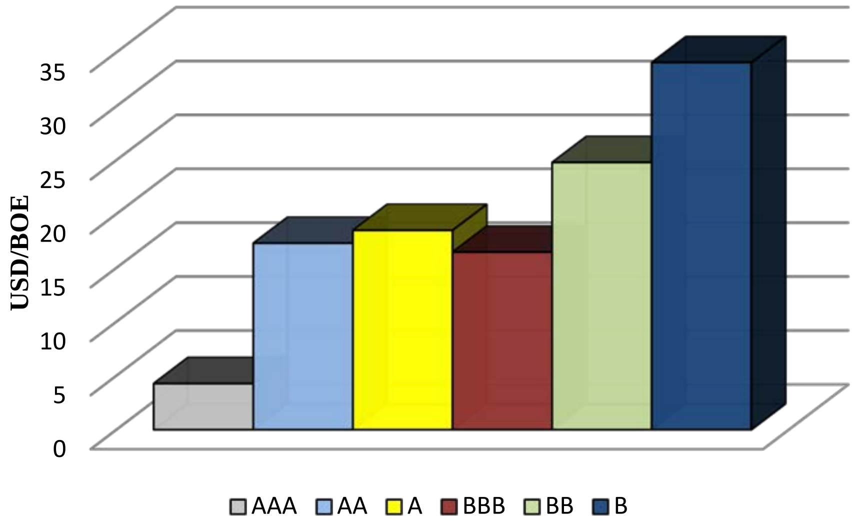
Where

$$Cash\ Flow\ from\ E\&P\ Activities$$
$$= Consolidated\ Cash\ Flow\ \times Revenue\ Share\ from\ E\&P\ Activities$$

Information on cash flow from each segment in companies that have operations midstream and downstream is generally not disclosed in annual reports. If the total cash flow is used directly in the aforementioned formula, CFBOE will be overstated for these companies because a major part of the company's cash flow could stem from mid- and downstream operations. To adjust for this, we have chosen to scale integrated companies' cash flows by the share of revenues the company has in the E&P segment compared to total revenues.

CFBOE indicates how much cash in US dollars each barrel of oil equivalent produced generates. This is a petroleum specific ratio that contains information on both liquidity position and on the efficiency of a company's E&P activities. Figure 5.3 shows the average CFBOE in each rating class:

Figure 5.3 Average CFBOE Differentiated on Rating Class –
Source: Datastream and 2012 Annual Reports



5.2.3 Interpreting the Final Model

Information on how well the full model fits our data set is presented in tables 5.4-5.6:

Table 5.4 Overall Model Fit

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	240.057			
Final	151.627	88.430	12	.000

Table 5.6 Individual Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	169.966	18.339	4	.001
CoverageRatio	172.053	20.426	4	.000
NETDEBTRATIO	166.562	14.935	4	.005
CashFlowperBOE	177.156	25.529	4	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Table 5.5 Pseudo R Square Final Model

Cox and Snell	.660
Nagelkerke	.697
McFadden	.368

The "Intercept Only" model tries to predict the observed frequencies in credit ratings without including independent variables. Such a model is analogous to the Total Sum of Squares (SST) in linear regression analysis (Menard, 1995, p. 20). In order to test whether the final model predicts observed frequencies with more accuracy than the "Intercept Only" model, a hypothesis test is performed. The null hypothesis is that the independent variables included are uncorrelated with credit ratings, and that the final model hence is not predicting the observed frequencies with more accuracy than the "Intercept Only" model. If the model is statistically significant, the null hypothesis is rejected and we conclude that the final model leads to better predictions of observed credit ratings.

The final model proposed is statistically significant at < 0.001 level, and we thus reject the null. As a result, there are relationships between some or all of the independent variables and the dependent variable that cannot be attributed to chance.

Table 5.5 shows the contribution to the predictive power of the final model made by each included financial ratio. For each financial ratio, the null hypothesis states that the inclusion of this ratio does not improve the fit of the model. Thus, we can conclude that the ratio in question improves the final model if the Chi-Square statistic exceeds the value corresponding to the predetermined alpha value. In our model, the three financial ratios included are all statistically significant at the <0.01 level, and we therefore conclude that each financial ratio encapsulates information that is influential for the credit rating of an E&P company.

Even though there is evidence of the relationship between credit ratings and the three included financial ratios in our model, we have thus far not analyzed the characteristics of these relationships. Table 5.7 shows parameter estimates for the full model:

Table 5.7 Parameter Estimates Final Model

Ratings[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp (B)	
								Lower Bound	Upper Bound
2.00	Intercept	-3.269	2.413	1.835	1	.176			
	CoverageRatio	-.313	.093	11.369	1	.001	.731	.610	.877
	NETDEBTRATIO	.143	.058	6.035	1	.014	1.154	1.029	1.293
	CashFlowperBOE	.191	.075	6.550	1	.010	1.210	1.046	1.401
3.00	Intercept	.536	2.167	.061	1	.805			
	CoverageRatio	-.192	.073	6.915	1	.009	.825	.715	.952
	NETDEBTRATIO	.076	.057	1.805	1	.179	1.079	.966	1.206
	CashFlowperBOE	.121	.071	2.868	1	.090	1.129	.981	1.298
4.00	Intercept	2.282	1.932	1.396	1	.237			
	CoverageRatio	-.072	.040	3.199	1	.074	.931	.860	1.007
	NETDEBTRATIO	.053	.051	1.059	1	.303	1.054	.953	1.166
	CashFlowperBOE	.048	.066	.533	1	.465	1.049	.922	1.195
5.00	Intercept	.096	2.049	.002	1	.962			
	CoverageRatio	-.041	.039	1.072	1	.300	.960	.889	1.037
	NETDEBTRATIO	.073	.055	1.752	1	.186	1.075	.966	1.198
	CashFlowperBOE	.056	.069	.664	1	.415	1.058	.924	1.210

a. The reference category is: 6.00.

As discussed in section 4.2, the multinomial logit model consists of M-1 equations. Rating class AA (category 6.00) is chosen as the reference category, and the coefficients in all four equations are calculated relative to this rating class. Exxon Mobil is the only company within our sample with an AAA rating, but this is recoded to AA due to the fact that the multinomial logit cannot handle the estimation of a case whose values on both the dependent variable and one or more of the independent variables is larger than all other values in the sample[29].

A coefficient B equal to zero indicates that there is no relationship between credit ratings and the financial ratio in question. Because the multinomial logit model is nonlinear, the interpretation of the coefficient is not as straightforward as in a linear model. In an attempt to provide an intuitive explanation of the relationship between credit ratings and the included financial ratios, we choose to interpret the model through odds ratios. An odds ratio is Euler's number raised to the power of the coefficient B, and indicates the change in odds of belonging to one rating class when the value on a financial ratio changes by one unit. Since a value of B equal to zero indicates an uncorrelated relationship between Y and $X_i$we know that an odds ratio equal to one indicates no change in the odds of belonging to the comparison group. A negative coefficient B leads to an odds ratio between zero and one, and thus indicates a decrease in the odds of belonging to the comparison group when the value of a financial ratio increases by one unit. Correspondingly, an odds ratio above 1 increases the odds of being in the comparison group if the financial ratio in question increases by one unit.

The farther an odds ratio of a financial ratio deviates from 1, the more powerful the relationship between credit ratings and the financial ratio. For example, an odds ratio equal to 1.7 indicates that the odds of belonging to the comparison group increases by 70 percent if the value on the financial ratio increases by one unit. Inversely, an odds ratio of 0.3 indicates an odds decrease of 70 percent when it comes to belonging in the comparison group.

When comparing companies rated AA with companies rated B all three financial ratios are statistically significant. CR has an odds ratio of 0.731, indicating that the odds of

[29] This was the case on Coverage Ratio for Exxon. While recoding potentially weakens the analysis, we strive to include all companies within Statoil's peer group. Exxon would have had to be taken out of the sample if recoding was not an option.

belonging to the B class decreases by 26.9 percent if the CR increases by one unit. This is in line with expectations, because a higher CR indicates an increased ability to pay the interest expenses on outstanding debt. Indirectly, an E&P company that either increases its operating profit or reduces its net finance charges appears more likely to increase its credit rating.

NDR has an odds ratio of 1.154, which suggests that an increase in NDR by one unit increases the odds of being in the B group by 15.4 percent. In other words, an E&P company that incurs more debt will tend to incur a downward pressure on its credit rating ceteris paribus. This is also in line with expectations, because more debt places larger restrictions on a company's cash flow. If the E&P industry experiences significant turmoil, an E&P company that is fully equity financed does not have to allocate a share of its cash flow to the shareholders in that particular period. A company that is fully financed by debt, on the other hand, will default if it does not repay its loan to external creditors. Existing restrictions on a company's cash flow are therefore likely to have a negative effect on an E&P company's credit rating, because it becomes more risky for a lender to allocate funds to that company.

CFBOE has a coefficient of 1.210, which indicates an increase in odds of belonging to the B class of 21 percent relative to the AA class if the CFBOE increases by one unit. This is surprising, since we would expect that creditworthiness, and thereby the credit rating, will increase when the cash flow generated by each barrel of oil equivalent increases. The results presented in Amdouni & Soumare (WP) are, however, in line with this result – Using a sample of Canadian corporations rated by S&P, they find that a more liquid firm is more likely to have a lower credit rating. One explanation for this result could be that "these firms are more likely to keep a higher level of liquidity in anticipation of possible funding difficulties, and that because of restrictive credit conditions imposed to these due to their poor rating category" (Amdouni & Soumare, WP). Another explanation for this result can be the approximation that was done when CFBOE was calculated, that is, scaling the total CFBOE by revenues from E&P operations for companies with operations in other segments than E&P. We will elaborate on this in chapter 6.

Since the odds ratio on CR deviates more from 1 than the odds ratios on the other two financial ratios, the CR appears to be a more powerful predictor of credit ratings than the other two financial ratios included when it comes to the comparison between companies rated AA and B.

When we compare the AA rating class against the BB class, only CR is statistically significant at the 0.05 level. Its odds ratio is 0.825, and thus indicates a decrease in the odds of belonging to the BB class of 17.5 percent if CR increases by one unit. In line with the analysis on the B class, the same relationship is not surprisingly present between AA rated companies and BB rated companies as well, albeit to a slightly lesser extent. None of the other coefficients in any of the other groups are statistically significant, and will thus not be interpreted. This is expected, as the difference in values on the selected financial ratios likely will be smaller when the difference in rating becomes smaller. Additionally, a sample size of 82 companies is not large enough to yield statistically significant odds ratios between all rating notches unless there are relatively extreme differences in the values of the included financial ratios across rating classes.

Table 5.8 shows how well the model's predictions coincide with the observed credit ratings:

Table 5.8 Model Classification Using Predictors Only

Observed	Predicted					
	2.00	3.00	4.00	5.00	6.00	Percent Correct
2.00	24	2	2	0	0	85.7%
3.00	7	2	7	0	0	12.5%
4.00	2	3	18	0	1	75.0%
5.00	0	2	5	1	0	12.5%
6.00	0	0	2	0	4	66.7%
Overall Percentage	40.2%	11.0%	41.5%	1.2%	6.1%	59.8%

By using the actual values on the three included financial ratios for each company within the sample, the model predicts the correct rating for 60 percent of the companies. The model appears to handle companies within the B, BBB and AA rating classes substantially better than companies rated BB or A. However, the percentage of cases predicted correctly must be complemented with *how poorly* the remaining cases are classified in order to evaluate the overall goodness of fit. Even though the model predicts 75 percent of the observed BBB companies correctly, the misclassified cases range from a predicted B-rating to an AA-rating. Such variability in predicted ratings among an actual rating class weakens the model, because a company can end up being severely misclassified.

If we reduce the dependent variable to only distinguish between investment grade and speculative grade, the overall percentage of correct classifications is 84.1 percent (see Appendix H). As a result, a breakdown of the dependent variable into a larger number of categories leaves the model more prone to classification errors. Nevertheless, the predictive power of the model appears to be relatively satisfactory if one keeps the number of financial ratios included in mind. A larger number of financial ratios will likely improve the model's ability to classify companies correctly, but such a model can cause undesired consequences when it comes to multicollinearity.

To test the robustness of our model on different samples with other characteristics, an out-of-sample test with 2011 data is conducted. The results are presented in tables 5.9-5.11:

Table 5.9 Log-Likelihood Tests 2011 Sample

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	208.462	18.115	4	.001
NetDebtRatio	205.587	15.240	4	.004
CoverageRatio	197.607	7.260	4	.123
CFBOE	213.280	22.933	4	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Table 5.10 Pseudo R Square 2011 Sample

Cox and Snell	.481
Nagelkerke	.508
McFadden	.223

Additional information on the out-of-sample test is presented in Appendix I. As observed in table 5.9, there is no longer evidence that the relationship between credit ratings and CR cannot be attributed to chance. The remaining two financial ratios are significant at the <0.01 level. The model classifies close to 50 percent of E&P companies correctly out-of-sample when the nine-point rating scale is used, and more than 83 percent correctly when the

Table 5.11 Classification Table 2011 Sample

Observed	Predicted					
	2.0	3.0	4.0	5.0	6.0	Percent Correct
2.0	21	4	4	0	0	72.4%
3.0	11	2	3	0	1	11.8%
4.0	6	0	15	0	1	68.2%
5.0	1	0	6	1	1	11.1%
6.0	0	0	3	1	2	33.3%
Overall Percentage	47.0%	7.2%	37.3%	2.4%	6.0%	49.4%

dependent variable is dichotomous (investment grade and speculative grade). Generally, the variability among misclassified cases does not seem to be larger for the out-of-sample test (see Appendix I). Consequently, the model shows a relatively good fit out-of-sample when the number of financial ratios included is taken into account.

Although the model appears to yield robust results, it does not capture all underlying determinants of credit ratings within the E&P industry. A perfect model is neither expected nor realistic – rating agencies have reiterated that the final rating "is a judgement of analysts. No computer can come up with a rating" (Horrigan, 1966). We have shown that financial ratios can provide interesting results through comparison across companies, but there are characteristics on the firm specific level that it is hard to imagine get encapsulated in historical ratios. This especially applies for companies that face severe risks that have not occurred yet. Operations in a country that is in a war can pose a major operational risk, and a future incident can affect financial results in a way that lowers the creditworthiness, and thereby the credit rating of the company. However if no incident has occurred to date, accounting based ratios from the past will not include such information. Another example is a company that has a state ownership that is likely to lead to a bailout if the company approaches bankruptcy. If the company in question has not reached a state where a bailout is needed, then the value of this guarantee from the government cannot be observed through the value of accounting based financial ratios. As a result, it appears impossible to make a perfect model when the predictors solely consist of financial ratios. Nevertheless we believe the model serves as a viable first step to analyse the credit rating variation observed in an industry where the usefulness of financial ratios with regards to credit ratings to our knowledge has not previously been analyzed empirically.

6. Limitations and Future Research

The model introduced in this thesis captures relationships between credit ratings and three financial ratios that cannot be attributed to chance. Nevertheless our results are subject to a number of limitations. This chapter seeks to expand on the limitations we believe need to be highlighted, as well as suggesting an idea for future research on the link between credit ratings and financial ratios in the E&P industry.

6.1 Limitations

6.1.1 Sample Size

The multinomial logit model presented in this thesis builds on a sample of 82 E&P companies. In order to assess whether such a sample size is sufficient to not degrade the results in the analysis, there is a need to investigate the requirements for sample size in both PCA and multinomial logistic regression. (Tabachnick & Fidell, 2013, p. 618) argue that as long as communalities are large, samples well below 100 cases are acceptable in a PCA. In our case, communalities are large and we therefore conclude that the sample size is large enough to yield robust results. Requirements regarding the sample size for the multinomial logit vary widely. Schwab (2002) indicates a minimum of 10 cases for each independent variable included in the model (Starkweather & Moske, n/d). Since we have a cases-to-variables ratio of 27.3[30], we conclude that the sample size is large enough to provide meaningful results from the multinomial logistic regression.

Even if the sample size does not degrade the results in our final model, a larger sample size would have improved the abilities of making statistical inferences across all rating classes. Moreover a larger number of cases could have made the models that included more financial ratios more compelling, presumably due to a larger number of statistically significant independent variables. As a result, we expect that a model that culminates from a larger sample can explain even more of the variation within credit ratings than our final model is capable of doing.

[30] 82/3=27.3

6.1.2 Linearity in the Logit

As discussed in section 5.2.3, the assumption about linearity in the logit needs to be tested after the variable selection is conducted. There are several procedures suggested when it comes to testing this assumption, and we will use the Box-Tidwell approach suggested by Hosmer and Lemeshow. The test is conducted by including interaction terms between each predictor and its natural logarithm in the multinomial logit model along with the original independent variables. If one or more of the interaction terms are statistically significant, the assumption is violated. Table 6.1 shows the likelihood ratio tests in the new regression equation:

Table 6.1 Test of Linearity in the Logit Assumption

Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	132.270	8.779	4	.067
NETDEBTRATIO	140.817	17.327	4	.002
CashFlowperBOE	134.110	10.620	4	.031
CoverageRatio	129.486	5.995	4	.200
LINLOGITNDR	140.101	16.610	4	.002
LINLOGITCFBOE	134.069	10.578	4	.032
LINLOGITCR	132.862	9.371	4	.052

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Two out of three interaction terms are statistically significant at the five percent level, and the linearity in the logit assumption is therefore violated. We acknowledge that this is a limitation in the final model, because a violation of this assumption could lead to type II errors – failing to include financial ratios that really are significant[31]. (Tabachnick & Fidell, 2013, p. 445) suggest to transform variables where the assumption of linearity in the logit is

[31] https://www.statisticssolutions.com/academic-solutions/resources/directory-of-statistical-analyses/assumptions-of-logistic-regression/

violated, but this will make the interpretation of the model less clear and we therefore choose to keep the variables in their current form.

6.1.3 Accounting Methods in the Oil and Gas Industry

Oil and gas companies residing in different geographical areas are subject to accounting standards that may lead to different treatment of exploration costs. This is because some accounting standards let companies choose between two different accounting methodologies. These are called successful efforts accounting and full cost accounting. While the full cost method is restricted under International Financial Reporting Standards (IFRS), the US General Accepted Accounting Principles (US GAAP) allows the use of both methods. Which of these methods that best capture underlying economic transactions is unresolved (see Bryant (2003) for an in-depth discussion).

Primarily, the difference between these two methods relates to how they treat exploration costs. While the successful efforts (SE) method expenses the costs of unsuccessful exploration, the full cost (FC) method capitalizes these costs. Consequently, companies using SE are likely to incur higher overall costs on their income statements when unsuccessful exploration occurs. Additionally, companies using FC are required to perform a ceiling test on proved properties every reporting period[32]. If, say, the oil price plunges dramatically, marginal fields that were recoverable on the initial price level are no longer economically feasible to operate. Such an event can lead to an estimated value of a company's assets that is lower than the book value of assets on that company's balance sheet. If this occurs, companies that use the full cost method are required to write down their assets. Consequently, while the full cost method capitalizes exploration costs regardless of the underlying operations' successfulness, impairment charges occur on the income statement to these companies if the value of their proved properties falls.

Because of the different handling of exploration costs, the choice of accounting method will affect each company's income and cash flows if unsuccessful exploration occurs. Companies using the full cost method are likely to incur a higher net income, since all exploration costs are capitalized. On the other hand, the denominator in balance sheet ratios will be higher compared to companies that use the successful efforts method. As a

[32] http://www.deloitte.com/assets/Dcom-UnitedStates/Local%20Assets/Documents/AERS/us_aers_ogspotlight_012414.pdf

consequence, the choice of accounting method can affect various companies' financial ratios, effectively making the comparison among companies less reliable.

In our sample, 58 companies use the successful efforts method and 26 companies use the full cost method. As a result we acknowledge that this could introduce a bias in our analysis, since we have not made adjustments to profitability- or liquidity ratios. However, the only ratios that S&P adjust for when it comes to the choice of accounting method are EBITDA-related ratios. There is only one such ratio included in our analysis and the bias compared to S&P's use of ratios need therefore not be very large. Furthermore, the model presented in this thesis should be easy to use by interested parties, and we believe a complex adjustment to neutralize the choice of accounting method will make the model less straightforward to use.

6.1.4 Petroleum Specific Financial Ratios

The main hypothesis in this thesis is that S&P's disclosed financial ratios explain more of the variation in credit ratings than other disclosed financial ratios. Two of these ratios are petroleum specific – Reserve Replacement Ratio (RRR) and Average Reserve Life Index (ARLI). After carrying out the analysis however, none of these two ratios are included among the selected variables. We believe this could have something to do with how these ratios are calculated. The majority of companies that use RRR and ARLI calculate a three year average because production (the denominator in the ratios) and the addition to proved reserves can vary substantially from year to year. Because extracting information from annual reports is an extremely time-consuming exercise when the sample consists of 82 companies, this thesis has only used information in annual reports from 2012. This could potentially weaken the accuracy of RRR and ARLI because years with extreme production can create potentially misleading values on these ratios. For example Vanguard Natural Resources had a RRR of 12.79 in 2012, which means that they replaced 1279 percent of their produced hydrocarbons that year. This was due to a large acquisition of resources in 2012 which inflated RRR substantially. A three year average is likely to cancel out some of these extreme observations, and this is likely to increase the reliability of both RRR and ARLI. As a result, our final model could understate the importance of these two financial ratios when it comes to explaining variation in credit ratings.

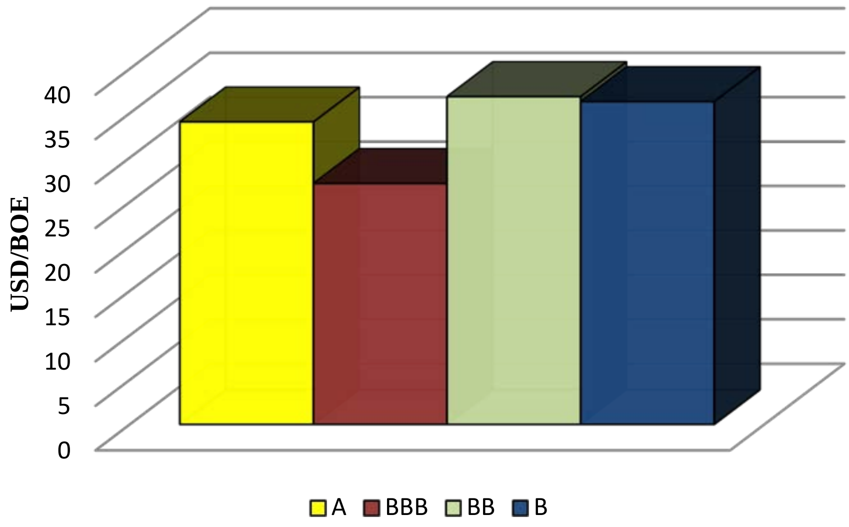
6.1.5 Approximations

In order to obtain comparable values, approximations were needed for several financial ratios. Most notably, this applied to ratios that have barrels of oil equivalent produced in its denominator – CFBOE, Profit per BOE and OPEX per BOE. This is due to the fact that roughly 50 percent of the companies within our sample are vertically integrated to some extent. Disclosed measures related to cash flow, profit and OPEX often address these companies' operations as a whole. Consequently, the numerator in these ratios also addresses the company as a whole, but the denominator (production) only addresses the upstream segment. In order to make these ratios comparable between integrated companies and pure E&P companies, the numerator in the ratio for the former need to be adjusted. We chose to focus on consistency and therefore adjusted the numerator in all of these ratios with the share of revenues generated in the E&P segment compared to total revenues.

Even though we view consistency in calculations as crucial, we acknowledge that this adjustment may be more appropriate for certain ratios compared to others. If the costs incurred for each dollar of revenue are not equal in upstream, midstream and downstream segments, the adjustment made for Profit per BOE will be somewhat inaccurate. The same applies for the CFBOE ratio – if revenue share is an inadequate approximation then the companies that are vertically integrated are likely to suffer inaccurate values on these ratios. This concern is mentioned in section 5.2.2.

The final model yielded unsurprising results except for one of the ratios included – CFBOE. For this ratio, we find that companies with lower values are likely to be located in the higher rating classes. We find this counterintuitive, and we want to test if the approximation discussed above could have had an effect on these results. To do this, we excluded all companies that have less than 95 percent of their operations in the upstream segment. Those companies are the ones affected by the approximation. 41 companies are left when these are taken out, and the average values on CFBOE on each rating class are presented in figure 6.1.

Figure 6.1 CFBOE Approximation Analysis -
Source: Datastream and 2012 Annual Reports



While the differences in average values appear smaller when the adjusted cases are taken out, the average values in both the B class and BB class are higher than the average values in the investment grade classes. However, the approximation method used appears to amplify the effect between investment grade classes and speculative classes, and we conclude that the CFBOE ratio therefore needs to be interpreted in a more cautious manner than the two other included ratios in the final model.

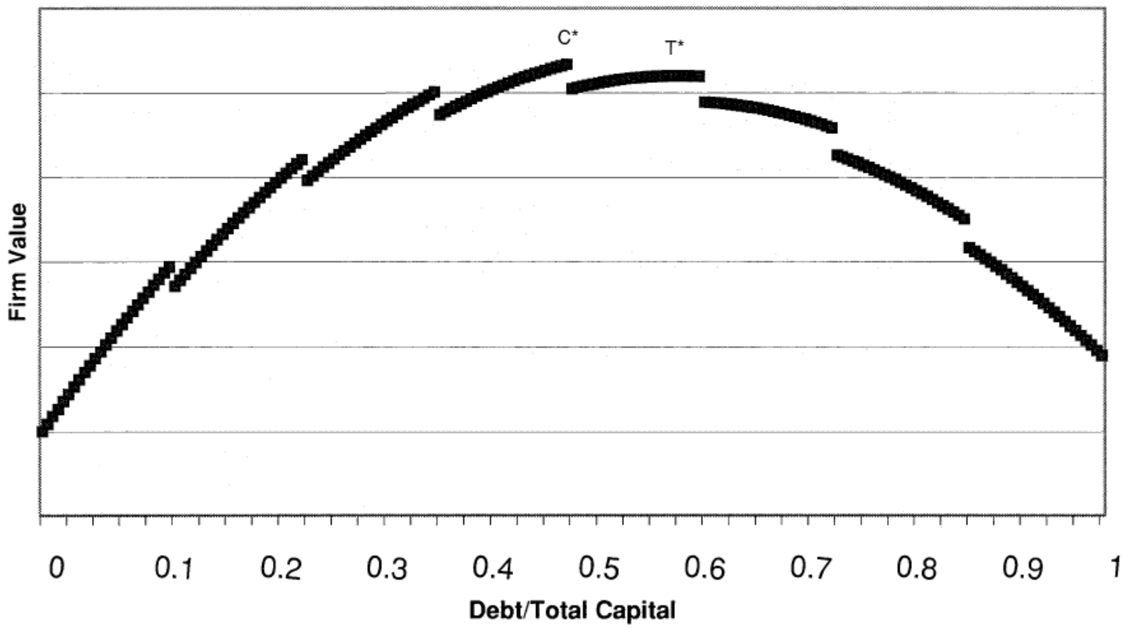
6.2 Future Research

Previous studies on the usefulness of financial ratios in explaining credit rating variation have often aspired to create a tool that can be used to estimate a credit rating for companies that are not rated by CRA's. Our research has a slightly different focus – we have created a model that is intended to serve as a tool for companies that are already rated[33]. A robust model that captures the main determinants of credit ratings could be useful in a number of ways for these companies. One application of such a model that has fascinated us relates to the link between credit ratings and capital structure.

[33] Of course, the model can also be used to estimate a non-rated company's credit rating.

Kisgen (2006) investigates the link between credit ratings and capital structure and concludes that firms near a downgrade or an upgrade issue less debt relative to equity compared to companies that are not near a rating change. The argument is that discrete costs and benefits with a rating change create a “notched” relationship between firm value and capital structure which is not consistent with the traditional tradeoff theory:

Figure 6.2 Tradeoff Theory and Discrete Costs (Benefits) at Multiple Credit Rating Levels - Source: Kisgen (2006)



Kisgen classifies companies with either a plus or a minus attached to its rating as “close to a rating change”, but we believe there is a significant leeway within each rating class assigned a plus or a minus when it comes to the chances of being downgraded or upgraded. This is where the research conducted in this thesis can become useful – if the most important determinants of credit rating variation are captured in a model consisting of a few financial ratios, the management of an E&P company has a straightforward tool to evaluate where they lie on a credit rating level. A simple example can show why this can be useful: If an E&P company has the opportunity to undertake a project that has a high NPV, but does not have the ability to finance this project from internally generated funds, obtaining financing through external debt could be a viable option. However, more debt increases the chances of being downgraded, which could force the company to pay a higher interest on debt and be forced to put up more collateral. As a result, we believe a model that evaluates whether a downgrade is dangerously close or not can yield substantial insight for the management of an E&P company.

The model created in this thesis is not directly suitable for such a research problem, however. First, our model is constructed by using 2012 data only. We believe the appropriate methodology to use would be a panel study, because it would allow the researcher to determine which financial ratios that explain most of the variation in ratings over a larger number of years. Second, a panel study would allow the researcher to reduce the number of companies in the sample. This could be beneficial because it may for instance not be appropriate to include small upstream companies in a model that is designed for the management of an oil major.

Our chosen research design is cross-sectional mainly because of how the data collection process is conducted – extracting information from annual reports. Access to WoodMac or Compustat would make the data collection much less time-consuming, and researchers that have these databases available could carry out a panel study rather swiftly. Additionally, these databases would make it possible to test one of the limitations in this thesis by using a multiyear average for the petroleum specific financial ratios RRR and ARLI.

7. Conclusions

We find that a non-linear model consisting of only three financial ratios captures a considerable share of the determinants in credit ratings assigned to E&P companies in 2012. Out-of-sample testing confirms the usefulness of the model, albeit to a slightly lesser extent than the in-sample results imply. None of the four financial ratios explicitly stated in S&P's corporate rating criteria - FFO/D, D/EBITDA, RRR and ARLI – are included in the final model, which suggests that the main hypothesis in this thesis does not appear to hold.

The three financial ratios included in our model are Net Debt Ratio, Coverage Ratio and Cash Flow per BOE. Our model predicts a higher probability of belonging to the lower rating classes when NDR is high and CR is low, which is in line with expectations. The surprising result is that the model implies that a high CFBOE increases the probability of belonging to a *lower* rating class.

Assigning credit ratings purely based on the values on the three financial ratios included in the model, the number of cases classified correctly is 59.8 in-sample and 49.4 out-of-sample. If the model is reduced to only distinguish between investment grade and speculative grade, the shares of correctly classified companies increase to 84.1 and 83.1 percent, respectively.

Although the model captures relationships between financial ratios and credit ratings that cannot be attributed to chance, the final model is subject to a number of limitations. In particular, we believe the explanatory power of RRR and ARLI – two of the ratios in S&P's corporate rating criteria – may be understated by solely relying on data from 2012. Additionally, some of the approximations that were necessary for calculations may have degraded or enhanced the explanatory power of certain financial ratios. Of the ratios in the final model, we believe this could be the case for CFBOE.

Despite its limitations, we believe the model can provide useful insight for both management in E&P companies and external parties that wish to assess the determinants of creditworthiness in the E&P industry in an intuitive way. Furthermore, the logic used in developing the model can be applied to evaluate the usefulness of financial ratios in explaining other complex phenomena such as the link between credit ratings and capital structure.

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Appendices

Appendix A: Formulas Used In Calculating Financial Ratios

$$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilities} \tag{A.1}$$

$$\begin{aligned} ROACE = (&Net\ Income - Bottom\ Line \\ &+ \big((Interest\ Expense\ on\ Debt - Interest\ Capitalized) \\ &\times (1 - Tax\ Rate)\big)) \\ &/(Average\ of\ Last\ Year's\ and\ Current\ Year's(Total\ Capital \\ &+ Short\ Term\ Debt\ \&\ Current\ Portion\ of\ Long\ Term\ Debt)) \end{aligned} \tag{A.2}$$

$$\begin{aligned} &ROE \\ &= \frac{(Net\ Income\ befor\ Preferred\ Dividends - Preferred\ Dividend\ Payment}{Last\ year's\ Common\ Equity} \end{aligned} \tag{A.3}$$

$$Dividend\ Yield = \frac{Dividends\ per\ share}{End\ of\ Year\ Share\ Price} \tag{A.4}$$

$$Payout\ Ratio = \frac{Dividends\ per\ share}{Earnings\ per\ share} \tag{A.5}$$

$$Net\ Debt\ Ratio = \frac{Net\ Debt}{Equity + Net\ Debt} \tag{A.6}$$

$$Interest\ Coverage\ Ratio = \frac{EBIT}{Before - Tax\ Interest\ Cost} \tag{A.7}$$

$$\begin{aligned} &Total\ Debt\ Ratio \\ &= \frac{Long\ Term\ Debt + Short\ Term\ Debt\ \&\ Current\ Position\ of\ Long\ Term\ Debt}{Total\ Capital + Short\ Term\ Debt\ \&\ Current\ Portion\ of\ Long\ Term\ Debt} \end{aligned} \tag{A.8}$$

$$Net\ Debt\ to\ Capital\ Employed = \frac{Net\ Debt}{Capital\ Employed} \tag{A.9}$$

$$Debt\ to\ EBITDA = \frac{Total\ Debt}{EBITDA} \tag{A.10}$$

$$Reserves\ Replacement\ Ratio = \frac{Amount\ Added\ to\ Proved\ Reserves}{Production} \tag{A.11}$$

$$DPR = \frac{Long\ term\ Debt + Current\ Portion\ Dividend}{Proved\ Developed\ Reserves} \tag{A.12}$$

$$Cash\ Flow\ per\ BOE = \frac{Results\ of\ Operations\ from\ E\&P - Depreciation - Depletion - Amortization - Impairment - Exploration\ Expenses}{Production} \tag{A.13}$$

$$F\&D\ Cost\ per\ BOE = \frac{(Aquisitions + Exploration + Development)_{Mill\$}}{(Drilling + Aquisitions + Revisions)_{MMBOE}} \tag{A.14}$$

$$Leverage\ Ratio = \frac{Net\ Debt}{Equity} \tag{A.15}$$

$$Coverage\ Ratio = \frac{Operating\ Profit}{Net\ Finance\ Charges} \tag{A.16}$$

$$Profit\ per\ BOE = \frac{Results\ of\ operations\ from\ E\&P\ Activities}{Production} \tag{A.17}$$

$$OPEX\ per\ BOE = \frac{OPEX\ Related\ to\ E\&P\ Activites}{Production} \tag{A.18}$$

$$Average\ Reserve\ Life\ Index = \frac{End\ of\ Year\ Proved\ Reserves}{Production} \tag{A.19}$$

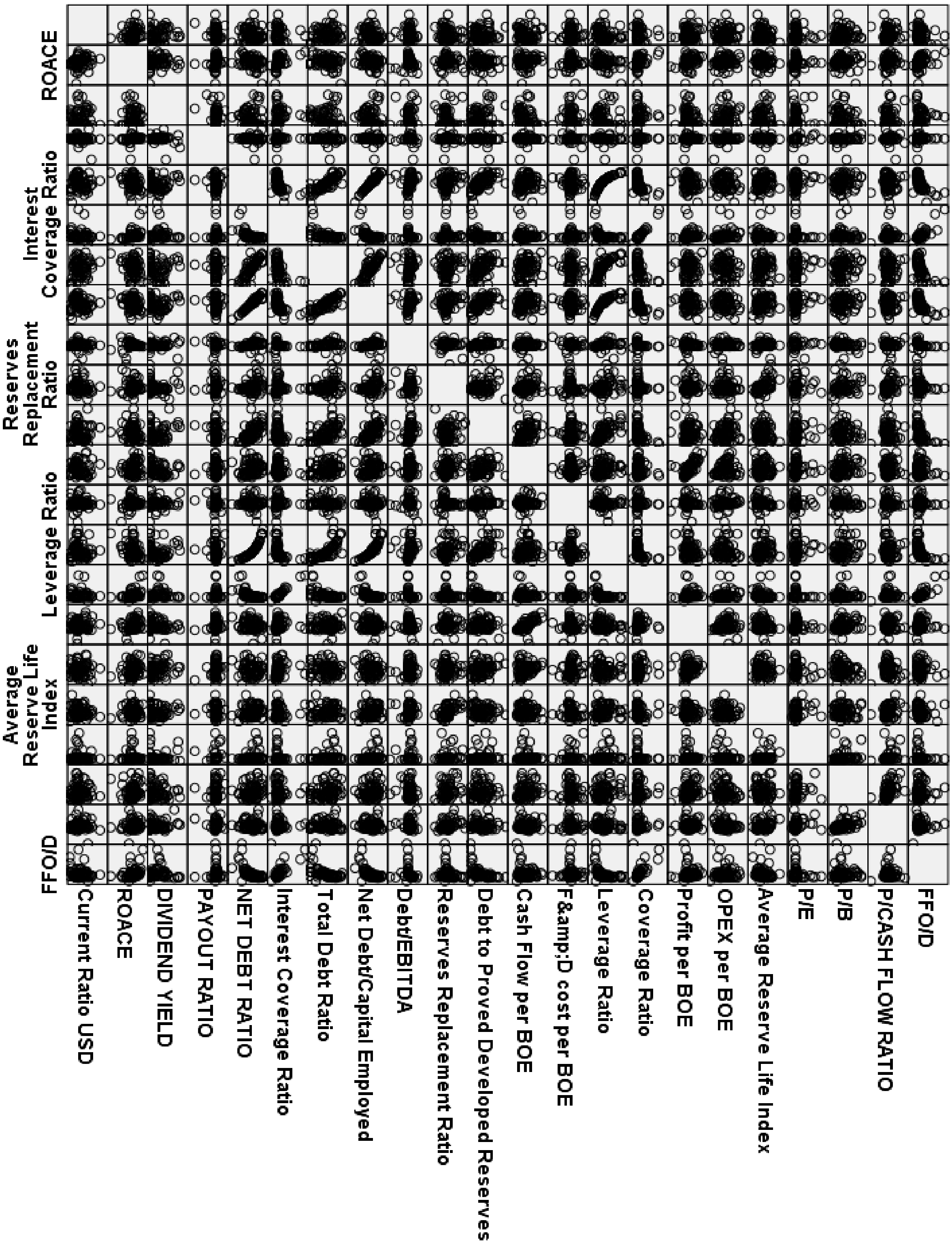
$$P/E = \frac{Share\ Price\ End\ of\ Year}{Earnings\ Per\ Share} \tag{A.20}$$

$$P/B = \frac{Share\ Price\ End\ of\ Year}{Book\ Value\ per\ Share} \tag{A.21}$$

$$P/CF = \frac{Share\ Price\ End\ of\ Year}{Cash\ Flow\ Per\ Share} \tag{A.22}$$

$$FFO/D = \frac{Funds\ From\ Operations}{Total\ Debt} \tag{A.23}$$

Appendix B: Bivariate Linearity Plots



Appendix C: Illustration of PCA

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.961	98.028	98.03	1.961	98.028	98.03
2	0.039	1.972	100.00	0.039	1.972	100.00

Extraction Method: Principal Component Analysis.

Appendix D – More on Eigenvalues and Eigenvectors

Calculating eigenvalues and eigenvectors by hand for a large matrix goes beyond both the scope of this thesis and the author's linear algebra abilities. However, calculation for a 2X2 matrix is illustrated here to give insight into how eigenvalues and eigenvectors are derived.

We will deal with the following 2X2 matrix:

$$A = \begin{bmatrix} 1 & 4 \\ 6 & 2 \end{bmatrix}$$

If we denote Δ as eigenvalues and ν as eigenvectors, then Δ is an eigenvalue of A if and only if $A\nu = \Delta\nu$ for some non-zero eigenvector ν. This is true if and only if:

$$\Delta \mathrm{I}\nu - A\nu = 0$$

Where I is the identity matrix.

The first step in finding eigenvalues is to multiply the identity matrix by Δ:

$$\Delta \mathrm{I} = \Delta \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} \Delta & 0 \\ 0 & \Delta \end{bmatrix}$$

We then subtract this expression from our initial 2X2 matrix and find the determinant of the matrix:

$$A - \Delta \mathrm{I} = \begin{bmatrix} 1-\Delta & 4 \\ 6 & 2-\Delta \end{bmatrix}$$

$$det \begin{bmatrix} 1-\Delta & 4 \\ 6 & 2-\Delta \end{bmatrix} = (1-\Delta)(2-\Delta) - (6)(4) = \Delta^2 - 3\Delta - 22$$

Setting the equation equal to zero, this can be written as:

$$(\Delta - 6.42)(\Delta + 3.42) = 0$$

Hence, the eigenvalues of this 2X2 matrix is 6.42 and -3.42.

To find the eigenvectors, we need to insert the eigenvalues in the 2X2 matrix:

$$\Delta = 6.42$$

$$\begin{bmatrix} 1-6.42 & 4 \\ 6 & 2-6.42 \end{bmatrix} = \begin{bmatrix} -5.42 & 4 \\ 6 & -4.42 \end{bmatrix}$$

If we call the new matrix B, we need to solve:

$$\begin{bmatrix} -5.42 & 4 \\ 6 & -4.42 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\left\{ \begin{matrix} -5.42 & 4 \\ 6 & -4.42 \end{matrix} \middle| \begin{matrix} 0 \\ 0 \end{matrix} \right\}$$

Using Gaussian elimination, we obtain the eigenvector $\begin{bmatrix} -0.67 \\ 0.74 \end{bmatrix}$. This is the eigenvector corresponding to the eigenvalue 6.42. The same procedure can be done when $\Delta = -3.42$ to obtain the second eigenvector.

Appendix E – KMO And Bartlett's Test of Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.683
Bartlett's Test of Sphericity Sig.	.000

Appendix F – Variance Explained By Principal Components

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.178	26.861	26.861	6.178	26.861	26.861	4.546	19.767	19.767
2	2.885	12.543	39.405	2.885	12.543	39.405	2.979	12.953	32.719
3	2.094	9.103	48.508	2.094	9.103	48.508	2.202	9.574	42.293
4	1.706	7.416	55.924	1.706	7.416	55.924	2.032	8.834	51.127
5	1.520	6.610	62.534	1.520	6.610	62.534	1.958	8.514	59.641
6	1.376	5.982	68.517	1.376	5.982	68.517	1.597	6.945	66.586
7	1.250	5.436	73.953	1.250	5.436	73.953	1.351	5.873	72.459
8	1.089	4.735	78.688	1.089	4.735	78.688	1.301	5.657	78.115
9	1.056	4.590	83.277	1.056	4.590	83.277	1.187	5.162	83.277
10	.920	4.002	87.279						
11	.642	2.792	90.071						
12	.547	2.376	92.447						
13	.408	1.775	94.222						
14	.345	1.501	95.723						
15	.260	1.132	96.855						
16	.231	1.006	97.860						
17	.173	.754	98.614						
18	.116	.506	99.120						
19	.096	.416	99.536						
20	.067	.291	99.827						
21	.020	.088	99.915						
22	.010	.044	99.958						
23	.010	.042	100.000						

Extraction Method: Principal Component Analysis.

Appendix G – More on Variables Selection Strategies

Correlations between credit ratings and each financial ratio are given in the following table:

Correlations

		Ratings
Ratings	Pearson Correlation	1
	N	82
Current Ratio USD	Pearson Correlation	.059
	Sig. (2-tailed)	.597
	N	82
ROACE	Pearson Correlation	.303
	Sig. (2-tailed)	.006
	N	82
ROE Percent	Pearson Correlation	.262
	Sig. (2-tailed)	.017
	N	82
DIVIDEND YIELD	Pearson Correlation	.262
	Sig. (2-tailed)	.018
	N	82
PAYOUT RATIO	Pearson Correlation	.128
	Sig. (2-tailed)	.251
	N	82
NET DEBT RATIO	Pearson Correlation	-.658
	Sig. (2-tailed)	.000
	N	82
Interest Coverage Ratio	Pearson Correlation	.588
	Sig. (2-tailed)	.000
	N	82
Total Debt Ratio	Pearson Correlation	-.538
	Sig. (2-tailed)	.000
	N	82
Net Debt/Capital Employed	Pearson Correlation	-.643
	Sig. (2-tailed)	.000
	N	82
Debt/EBITDA	Pearson Correlation	-.083
	Sig. (2-tailed)	.461
	N	82
Reserves Replacement Ratio	Pearson Correlation	-.377
	Sig. (2-tailed)	.000
	N	82
Debt to Proved Developed Reserves	Pearson Correlation	-.531
	Sig. (2-tailed)	.000
	N	82
Cash Flow per BOE	Pearson Correlation	-.435
	Sig. (2-tailed)	.000
	N	82
F&D cost per BOE	Pearson Correlation	.022
	Sig. (2-tailed)	.842
	N	82
Leverage Ratio	Pearson Correlation	-.609
	Sig. (2-tailed)	.000
	N	82
Coverage Ratio	Pearson Correlation	.615
	Sig. (2-tailed)	.000
	N	82
Profit per BOE	Pearson Correlation	.038
	Sig. (2-tailed)	.737
	N	82
OPEX per BOE	Pearson Correlation	.157
	Sig. (2-tailed)	.160
	N	82
Average Reserve Life Index	Pearson Correlation	-.205
	Sig. (2-tailed)	.065
	N	82
P/E	Pearson Correlation	-.190
	Sig. (2-tailed)	.087
	N	82
P/B	Pearson Correlation	-.104
	Sig. (2-tailed)	.351
	N	82
P/CASH FLOW RATIO	Pearson Correlation	-.057
	Sig. (2-tailed)	.608
	N	82
FFO/D	Pearson Correlation	.543
	Sig. (2-tailed)	.000
	N	82

Correlations between credit ratings and each financial Principal Component are given in the following table:

Correlations

		Ratings
Ratings	Pearson Correlation	1
	N	82
PC1	Pearson Correlation	-.505
	Sig. (2-tailed)	.000
	N	82
PC2	Pearson Correlation	.490
	Sig. (2-tailed)	.000
	N	82
PC3	Pearson Correlation	-.227
	Sig. (2-tailed)	.040
	N	82
PC4	Pearson Correlation	.197
	Sig. (2-tailed)	.076
	N	82
PC5	Pearson Correlation	-.203
	Sig. (2-tailed)	.067
	N	82
PC6	Pearson Correlation	.066
	Sig. (2-tailed)	.553
	N	82
PC7	Pearson Correlation	-.027
	Sig. (2-tailed)	.812
	N	82
PC8	Pearson Correlation	-.050
	Sig. (2-tailed)	.658
	N	82
PC9	Pearson Correlation	-.090
	Sig. (2-tailed)	.422
	N	82

Information on each variable selection strategy is presented in the following:

Strategy 1: Since the only concern is related to each financial ratio's loading on the PCs, the included ratios are observable directly from Table 6.1 Rotated Component Matrix. Consequently, we will not explain this strategy any further.

Strategy 2: Detailed data on how to find the variables included in the model is presented in the following tables:

Ratios with Loading on First PC	Factor Loading	Correlation with Dependent Variable	SCORE
Net Debt Ratio	*0.91*	*(0.66)*	*0.79*
Total Debt Ratio	*0.87*	*(0.54)*	*0.70*
Net Debt/Capital Employed	*0.88*	*(0.64)*	*0.76*
Debt to Proved Developed Reserves	*0.75*	*(0.53)*	*0.64*
Leverage Ratio	*0.91*	*(0.61)*	*0.76*
Coverage Ratio	*(0.30)*	*0.62*	*0.46*
Price/Book	*0.30*	*(0.10)*	*0.20*
Funds from Operations/Debt	*(0.45)*	*0.54*	*0.50*

Ratios with Loading on Second PC	Factor Loading	Correlation with Dependent Variable	SCORE
Interest Coverage Ratio	*0.91*	*0.59*	*0.75*
Coverage Ratio	*0.91*	*0.62*	*0.76*
Funds from Operations/Debt	*0.82*	*0.54*	*0.68*

Ratios with Loading on Third PC	Factor Loading	Correlation with Dependent Variable	SCORE
Dividend Yield	*(0.46)*	*0.26*	*0.36*
Cash Flow per BOE	*0.86*	*(0.44)*	*0.65*
Profit per BOE	*0.85*	*0.04*	*0.44*
Price/Book	*0.41*	*(0.10)*	*0.26*

Ratios with Loading on Fourth PC	Factor Loading	Correlation with Dependent Variable	SCORE
Current Ratio	*0.70*	*0.06*	*0.38*
ROACE	*0.80*	*0.30*	*0.55*
ROE	*0.79*	*0.26*	*0.53*

Ratios with Loading on Fifth PC	Factor Loading	Correlation with Dependent Variable	SCORE
Reserves Replacement Ratio	*0.79*	*(0.38)*	*0.58*
Average Reserve Life Index	*0.89*	*(0.21)*	*0.55*
Price/Cash Flow	*0.51*	*(0.06)*	*0.28*

Ratios with Loading on Sixth PC	Factor Loading	Correlation with Dependent Variable	SCORE
Dividend Yield	*0.42*	*0.26*	*0.34*
Debt to Proved Developed Reserves	*0.40*	*(0.53)*	*0.46*
OPEX per BOE	*0.86*	*0.16*	*0.51*
Price/Book	*(0.53)*	*(0.10)*	*0.32*

Ratios with Loading on Seventh PC	Factor Loading	Correlation with Dependent Variable	SCORE
Dividend Yield	*0.42*	*0.26*	*0.34*
Payout Ratio	*(0.82)*	*0.13*	*0.47*
Price/Cash Flow	*0.49*	*(0.06)*	*0.27*

Ratios with Loading on Eight PC	Factor Loading	Correlation with Dependent Variable	SCORE
F&D Cost per BOE	*0.75*	*0.02*	*0.39*
Price/Earnings	*0.74*	*(0.19)*	*0.46*

Ratios with Loading on Ninth PC	Factor Loading	Correlation with Dependent Variable	SCORE
Current Ratio	*(0.32)*	*0.06*	*0.19*
Debt/EBITDA	*0.86*	*(0.08)*	*0.47*
P/B	*(0.33)*	*(0.10)*	*0.22*

Retained Financial Ratios	
PC1	*Net Debt Ratio*
PC2	*Coverage Ratio*
PC3	*Cash Flow per BOE*
PC4	*ROACE*
PC5	*Reserves Replacement Ratio*
PC6	*OPEX per BOE*
PC7	*Payout Ratio*
PC8	*Price/Earnings*
PC9	*Debt/EBITDA*

Strategy 3: The retained PCs that correlate with Y at the 0.05-level and the financial ratios that has the highest loading on each of these PCs are presented in the following table:

Components Correlated with Y	Ratios With Highest Loading
PC1	*Net Debt Ratio*
PC2	*Coverage Ratio*
PC3	*Cash Flow per BOE*
PC4	*ROACE*
PC5	*Average Reserve Life Index*

Strategy 4: All financial ratios that correlate significantly with Y at the 0.05-level are presented in the following table. Additionally, the financial ratios with the highest loading among significant ratios are presented.

Significant Correlations with Y
ROACE
ROE
Dividend Yield
Net Debt Ratio
Interest Coverage Ratio
Total Debt Ratio
Net Debt/Capital Employed
Reserves Replacement Ratio
Debt to Proved Developed Reserves
Cash Flow per BOE
Coverage Ratio
Leverage Ratio
FFO/D

PC Number	Ratios With Highest Loading
PC1	*Net Debt Ratio*
PC2	*Coverage Ratio*
PC3	*Cash Flow per BOE*
PC4	*ROACE*
PC5	*Reserves Replacement Ratio*
PC6	*Dividend Yield*
PC7	-
PC8	-
PC9	-

Appendix H – Classification Table with a Dichotomous Dependent Variable

Classification

Observed	Predicted .00	Predicted 1.00	Predicted Percent Correct
.00	39	5	88.6%
1.00	8	30	78.9%
Overall Percentage	57.3%	42.7%	84.1%

Appendix I – Out-of-Sample Tests

The companies included for the out-of-sample test were the same as the companies included in the initial sample.

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	244.838			
Final	190.347	54.491	12	.000

Ratings[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp (B)	
								Lower Bound	Upper Bound
2.0	Intercept	-2.725	1.635	2.777	1	.096			
	NetDebtRatio	.112	.042	7.149	1	.008	1.118	1.030	1.213
	CoverageRatio	-.033	.026	1.542	1	.214	.968	.919	1.019
	CFBOE	.125	.049	6.446	1	.011	1.134	1.029	1.249
3.0	Intercept	-.956	1.525	.393	1	.531			
	NetDebtRatio	.062	.040	2.368	1	.124	1.064	.983	1.152
	CoverageRatio	-.044	.027	2.721	1	.099	.957	.908	1.008
	CFBOE	.108	.049	4.806	1	.028	1.114	1.011	1.226
4.0	Intercept	1.843	1.255	2.158	1	.142			
	NetDebtRatio	.021	.035	.363	1	.547	1.021	.953	1.095
	CoverageRatio	-.045	.022	4.137	1	.042	.956	.916	.998
	CFBOE	.039	.047	.668	1	.414	1.039	.947	1.140
5.0	Intercept	-.107	1.348	.006	1	.937			
	NetDebtRatio	.040	.037	1.177	1	.278	1.041	.968	1.120
	CoverageRatio	-.014	.017	.707	1	.400	.986	.954	1.019
	CFBOE	.043	.049	.756	1	.385	1.044	.948	1.149

a. The reference category is: 6.0.

Summary statistics when the dependent variable is recoded into two categories are presented in the following tables:

Observed	Predicted .00	Predicted 1.00	Predicted Percent Correct
.00	39	7	84.8%
1.00	7	30	81.1%
Overall Percentage	55.4%	44.6%	83.1%

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	114.085			
Final	76.523	37.562	3	.000

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	90.103	13.580	1	.000
NetDebtRatio	86.128	9.605	1	.002
CoverageRatio	77.137	.615	1	.433
CFBOE	97.841	21.318	1	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Cox and Snell	.364
Nagelkerke	.487
McFadden	.329

VAR00001[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp (B)	
								Lower Bound	Upper Bound
.00	Intercept	-3.051	.987	9.561	1	.002			
	NetDebtRatio	.061	.023	6.994	1	.008	1.063	1.016	1.111
	CoverageRatio	-.012	.017	.539	1	.463	.988	.955	1.021
	CFBOE	.081	.022	14.223	1	.000	1.085	1.040	1.131

a. The reference category is: 1.00.