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Bankruptcy Prediction with Financial Ratios

- Examining Differences across Industries and Time

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Abstract

Title:	Bankruptcy Prediction with Financial Ratios – Examining Differences across Industries and Time.
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Authors:	David Lundqvist and Jakob Strand
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Five key words:	Credit Risk, Bankruptcy Prediction Modeling, Logit Regression, Financial Ratios, Industry Differences
Purpose:	The purpose of this study is to examine how well different financial ratios can predict bankruptcy across industries and time. The study also examine whether including industry differences in a prediction model can increase its accuracy.
Methodology:	Bankruptcy prediction models were estimated using logistic regression for each year between 2006 and 2011, with and without interaction terms accounting for industry effects. These were analyzed and tested on a holdout sample for their classification abilities.
Theoretical perspectives:	This study is influenced by previous research within bankruptcy prediction modeling performed by for example Ohlson (1980).
Empirical foundation:	311,930 annual reports from non-bankrupt companies and 5,257 annual reports from bankrupt companies were analyzed, covering the time period 2006 to 2011.
Conclusions:	The study shows that the bankruptcy-prediction ability of different financial ratios varies between years. However, only in some cases, significant differences between industries were found. The overall classification ability was not significantly increased when including the industry effects but using some specified cut-off values, a marginal increase was found.

Acknowledgement

The working process of this study has been rewarding in many ways and we have broadened our knowledge of statistical methodology and credit risk modeling.

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Contents

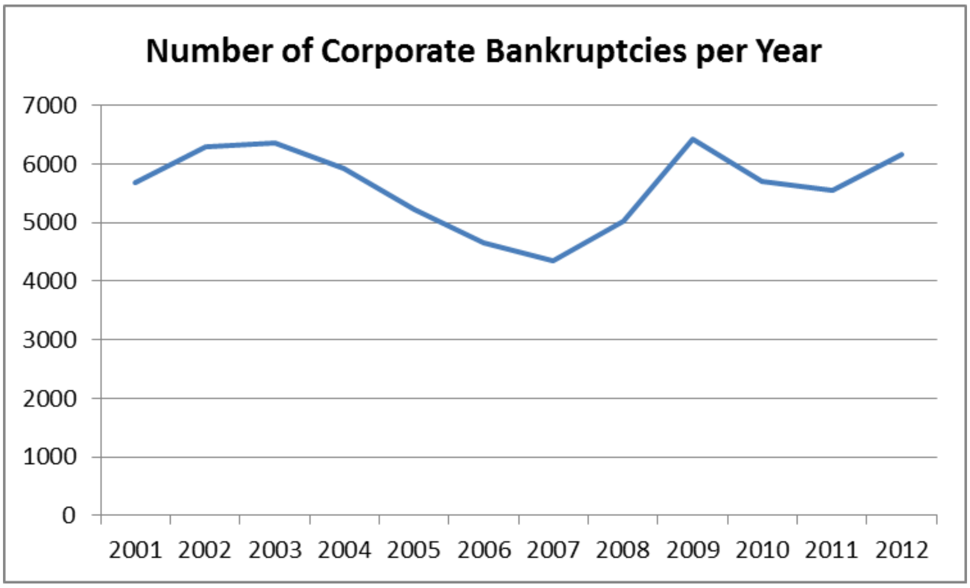
1 INTRODUCTION

This chapter starts with a short background to the subject. Next a problem discussion follows that lead up to the research questions, purpose and delimitations of the study. The chapter ends with a short presentation of the thesis outline.

1.1 Background

Every year, thousands of companies find themselves in financial difficulties which in many cases lead to bankruptcy. Over the last decade the number of bankruptcies in Sweden has followed a cyclical pattern. After the IT bubble burst in the beginning of the millennia the number was on top but then steadily decreased until the new crisis hit the world economy in 2008. In 2009 the number of bankruptcies in Sweden peaked at 6,428 bankruptcies and has since then decreased to a number of 6,163 in 2012. Figure 1.1 illustrates how the bankruptcies have evolved over time (The Swedish Agency for Growth Policy Analysis, 2013).

Figure 1.1

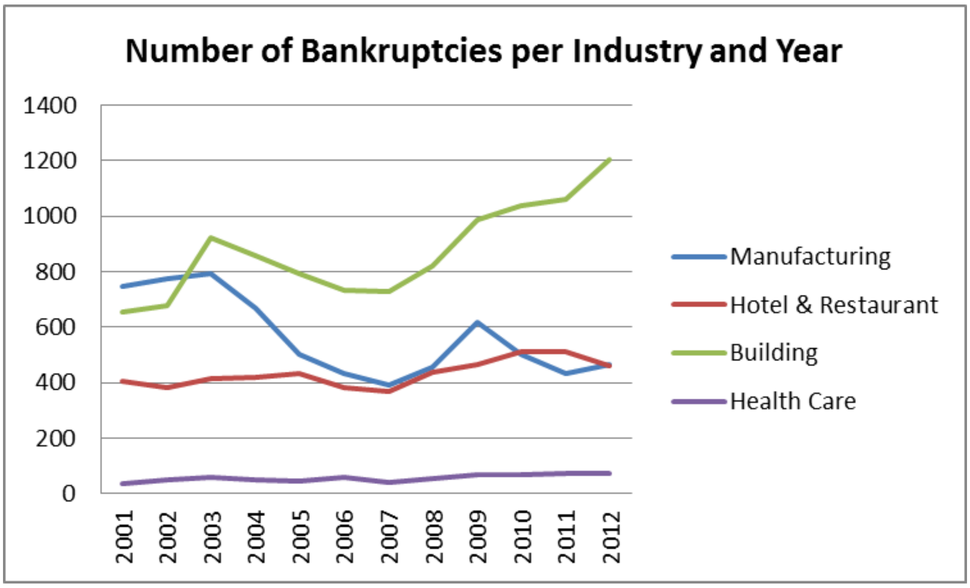


Number of corporate bankruptcies per year in Sweden between 2001 and 2012

This development has also been observed among people working with bankruptcies. Lena Kulling, functional manager at the Collections department at Swedbank, describes a similar pattern. According to her, they experienced a peak of bankruptcies among their borrowers in 2008 thereafter followed by a decline (personal communication, 2013-02-25).

The development of bankruptcies has not looked the same across industries. Figure 1.2 below illustrates how the number of bankruptcies for four different industries has developed over the last decade (The Swedish Agency for Growth Policy Analysis, 2013).

Figure 1.2



Number of bankruptcies per year in Sweden within four industries

Clearly, there are differences across industries. These differences also affect the investors and their willingness to invest money in the industries. According to Torbjörn Johansson, a credit specialist with experience of credit granting at Swedbank, they can be very skeptical granting loans to some industries such as the newly deregulated and highly competitive pharmaceutical industry (personal communication, 2013-02-25).

There are many theories and arguments for why companies go bankrupt. Schumpeter (1942) called it "creative destruction", a process of industrial mutation where new economic structures are destroying old ones. According to this philosophy, bankruptcies are a natural part of the capitalism and make it possible for new companies and industries to grow. Bankruptcies are a major phenomenon in the economy and many would probably admit that they can be problematic. Not only a firm's investors are affected by a bankruptcy but also other stakeholders. For example, in 2012, 25,466 employees in Sweden were affected by the bankruptcy of their employer (The Swedish Agency for Growth Policy Analysis, 2013).

Whether or not bankruptcies are seen as problematic, it is valuable for stakeholders to know the risk of a corporate bankruptcy. Investors may want to incorporate the risk into the required rate of return and employees may want to start looking for another job. A firm's suppliers may want to know the risk before granting trade credits. For these and many other stakeholders, a lot of tools for risk evaluations exist.

1.2 Problem Discussion

The situations are many in which credit risk evaluations are necessary. Stakeholders in need for such evaluations have two options. Either they can rely on existing credit ratings offered by credit rating agencies such as Moody's, or they can make their own evaluations.

Credit rating agencies have been criticized on a number of areas. First of all, their competence has been questioned after a number of misjudgments or failures such as not being able to detect the true financial condition of Enron (Frost, 2007). There have also been questions whether rating agencies can manage the conflict of interest of having an economic interests in basing a credit rating on anything else than creditworthiness (Frost, 2007). However, such a problem has been tested for without any evidence of its existence (Covitz & Harrison, 2003).

If one decides to make their own credit risk evaluation he or she has different available models to utilize. One type of credit risk models are the market-based models. These models employ option-pricing theory to make estimates of corporate default (Charitou et al., 2008). A problem with these models is that they cannot be applied directly on privately held companies since they depend on market values and the volatility in market value returns.

Another option is to use an evaluation model based on accounting data. Over the last 50 years a lot of empirical studies have been made within this field of bankruptcy prediction modeling.

Altman (1968) was the first one to use multivariate statistical modeling in his "Z-score model" to find combinations of financial ratios that can indicate bankruptcy risk. The ratios included in Altman's model were for example a return on assets ratio and a leverage ratio. Another model was estimated by Ohlson in 1980. He utilized a method not previously used in the bankruptcy prediction research called logistic regression and modeled different financial ratios such as liquidity and leverage. After him, a lot of researchers have performed similar studies. However, many of the existing models are very general and are estimated from a sample of companies from different industries without much consideration to how these industry differences may affect the results.

One reason why general models may be less accurate compared to industry-adapted models can be understood by examining the average financial ratios among different industries. For example, the sales-to-assets ratio is on average 1.72 for wholesale and retail firms in the US but 0.54 for manufacturing firms (Brandow Company, 2013). This ratio was included in Altman's (1968) original Z-score model with a positive coefficient, indicating that a higher value leads to a higher Z-score and a lower risk of bankruptcy. Applying Altman's model on these two industries would therefore (all other variables being equal) yield lower Z-scores for the manufacturing industry, even though the bankruptcy risk may not be higher in this industry. It is reasonable to think that there is a structural difference between these two industries that can explain at least parts of this difference in averages. A manufacturing company probably needs much more machines and other assets to be able to produce and sell their goods, while a retail company only distributes goods and does not produce much on their own. By understanding these differences in ratios between industries, better bankruptcy risk estimation can hopefully be made.

Another problem is related to the time dimension. Altman (1968) used a data sample covering 20 years, and Ohlson's (1980) sample covered 7 years. Pooling financial data from many years in this way will lead to that both historical and recent financial data will be considered of equal weight and that the time dimension is lost. By analyzing differences in financial ratios and their predictive ability across years, the severity of pooling data can be further understood.

1.3 Research Questions

- How does the bankruptcy-prediction ability for a set of common financial ratios vary across a number of industries and across time?
- Do incorporating industry-variations change the performance of a bankruptcy-prediction model compared to a model without these variations?

1.4 Purpose

The main purpose of this thesis is to study how financial ratios can have different bankruptcy-indicating abilities across industries and time. The goal is to estimate models in a similar way as Ohlson (1980) did, and then add industry-depending interaction terms and dummies to count for the differences between industries. The final purpose is to compare the prediction accuracy of the estimated models to see what effect the industry-adaptation can have on the results. The results from this study can hopefully increase the understanding among business researchers and academics on how financial ratios vary as bankruptcy indicators across industries and time, and inspire researchers for further research. Hopefully the results can also serve as a new tool for some market participants in need for a better way to predict corporate bankruptcy.

1.5 Delimitations

This study will only focus on how an empirically estimated model for bankruptcy prediction based on logistic regression can be adapted to and explain industry differences. Alternative models or estimation techniques will not be examined. The companies studied are privately held Swedish companies. Sweden was chosen as the target because of the rich amount of financial data available through the Swedish Companies Registration Office. To be able to model industry characteristics, only five industries were chosen for this further analysis. These five industries are presented in section 3.3.1. The study can hopefully increase the understanding on how different financial ratios can indicate bankruptcy across the five chosen industries and how they vary over time. The study will not be able to answer questions regarding how other factors such as "soft variables" or macroeconomic conditions can explain bankruptcies.

1.6 Thesis Outline

The upcoming chapter will introduce the reader to fundamental concepts and models within the bankruptcy literature. Previous studies concerning industry differences and the attempts to incorporate these into prediction models will also be discussed. Chapter 3 describes the methodology used in this study. Step by step the process that lead up to the results is described. The results of the study will be presented in chapter 4, analyzed in chapter 5, and finally concluded in chapter 6.

2 THEORETICAL FRAMEWORK

This chapter starts with a discussion on terminology and a brief review of bankruptcy legislation. Next, a number of accounting-based, market-based and hazard models will be reviewed to outline their fundamental differences, followed by a review of some studies on industry-differences. In the end, a hypothesis for the study is presented.

2.1 Corporate Default and Failure

Default is a common word in the literature, often associated with the potential negative event in a situation where credit risk is present. According to the Dictionary of Finance and Banking (Oxford Reference, 2012), default can be defined as *the failure to make required payments*.

Default does not automatically lead to bankruptcy though. Many companies fail to make required payments on loans because of temporary illiquidity, and these companies can often negotiate with the bank to find another solution than to go bankrupt. According to Jens Skaring, head of the Financial Restructuring and Recovery department at Swedbank, they can for example postpone the reinstallments or renegotiate the interest rate (personal communication, 2013-03-06).

Failure is another common word, particularly within accounting-based modeling literature. Beaver (1966) defined failure as *the inability of a firm to pay its financial obligations as they mature* – a definition similar to the definition of *default* presented above. Altman (1968) and Ohlson (1980) on the other hand used the term *failure* in a legal perspective on companies that have filed for bankruptcy. Skogsvik (1990) finally, associated failure not only with legal bankruptcy but also with composition agreements, voluntary shut-downs of primary production activities and receipt of substantial subsidies from the state.

Clearly, there are many terms and definitions being used. Since the definition of failure is often the basis for the selection of companies to study in the bankruptcy research, the definition used affects the results and the conclusions that can be made.

The definition of *failure* used in this study is similar to the definition used by Altman (1968) and Ohlson (1980). Companies that have failed are companies that have filed for bankruptcy and begun or ended their bankruptcy process. Companies that have been voluntary shut down are not considered failed companies since no information are held on what cause is behind the shut-down.

2.2 Bankruptcy Regulations

In order to understand which firms can be classified as bankrupt and what conditions that can start this process, it is a good idea to study the bankruptcy regulations. Since this study is performed on Swedish companies, the Swedish regulatory framework will be examined. A company experiencing liquidity issues can either apply for reconstruction or bankruptcy. In the case of bankruptcy the creditors will forcefully claim the assets of the bankrupt company as payment on the outstanding debt. A debtor can by himself and by the request of a creditor be put into bankruptcy[1]. A creditor can file for the bankruptcy of a company if the debtor is insolvent. If nothing else is said, a debtor is insolvent if the debtor 6 months prior to the filing have not been able to meet their financial obligations or has been urged by the creditor to pay its debt but neglected to do so for one week[2]. However, the creditor is unable to file for bankruptcy of the debtor if collateral is held, if a third party secures the debt on behalf of the creditor, or the debt have not yet defaulted and a third party insures its payment[3].

When the bankruptcy request is accepted by the district court an independent administrator that holds the appropriate expertise and experience is selected by the court to oversee the bankruptcy. Depending on the company one or more administrators can be appointed[4]. According to Tomas Gustafsson, manager at the Collections department at Swedbank, a bankruptcy process takes on average 1.5-2 years but depending on the size of the company a bankruptcy process can stretch out for much longer periods. Bankruptcy filings are not the first course of action when a company meets liquidity problems. Rather than liquidation, the possibility of a restructuration is examined and is a preferred alternative in many cases (personal communication, 2013-02-25).

2.3 Credit Risk Models

There are two major groups of models for evaluating corporate credit risk. The first group consists of accounting-based models. These models can be used to predict corporate failure and are empirically estimated from a sample of failed and non-failed

[1] Konkurslag (1987:672), 1 §, 2 §
[2] Konkurslag (1987:672), Kap 2. 7-9 §
[3] Konkurslag (1987:672), Kap 2. 10 §
[4] Konkurslag (1987:672), Kap 7. 1-2 §

companies. The other group consists of market-based models. These models on the other hand rely on a theoretical foundation and use option-pricing theory to value corporate liabilities and measure the probability of default. This section reviews the different kinds of models and their characteristics.

2.3.1 Accounting-Based Models

The accounting-based models use information from financial statements, normally in the form of ratios, to describe the risk of failure of a company. One of the first researchers to explore the predictive ability of financial ratios was Beaver (1966). He did a univariate analysis and examined a sample of 79 failed companies, including both bankrupt companies and companies with other financial problems. He found that cash flow/total debt and net income/total assets were the two best predictors of failure.

The first multivariate model for bankruptcy classification was presented by Altman (1968). This model, called Altman’s Z-score model, was based on a statistical method called multiple discriminant analysis (MDA). Altman used a sample of 66 companies, of which 33 were companies that had filed for bankruptcy. For each company, he calculated their values on five different financial ratios. Based on this data, a model was estimated that was able to classify a company as either a non-bankrupt company or a company that would go bankrupt within 1-2 years. More specifically, this classification was made by calculating a Z-score and then comparing it to a cut-off value. Companies with a higher Z-score than the cut-off value was classified as non-bankrupt while companies with lower Z-scores were classified as bankrupt. The five financial ratios that were included in the function are presented in table 2.1 below.

Table 2.1

Altman's Z-Score Model		Ohlson's Model	
Variable	**Definition**	**Variable**	**Definition**
X_1	(Current assets – current liabilities)/total assets	SIZE	Ln(total assets/GNP price-level index)
X_2	Retained earnings/total assets	TLTA	Total liabilities/total assets
X_3	EBIT/average total assets	WCTA	Working capital/total assets
X_4	MV of equity/BV of liabilities	CLCA	Current liabilities/current assets
X_5	Sales/average total assets	OENEG	1 if total liabilities exceeds total assets, 0 otherwise
		NITA	Net income/total assets
		FUTL	Funds from operations/total liabilities
		INTWO	1 if net income was negative for the last two years, 0 otherwise
		CHIN	Change in net income

The table shows the variables that were included in Altmans (1968) and Ohlson's (1980) model

After Altman, a lot of other researchers have performed similar studies. Deakin (1972) concluded that the predictive ability of Altman's model declined as the number of years prior bankruptcy increased and estimated models for each of the last five years prior company bankruptcy. Taffler (1982) on the other hand estimated a model for bankruptcies in the UK.

Ohlson (1980) criticized Altman and other previous researchers using MDA for predicting bankruptcy. Using MDA imposes a lot of statistical assumptions that are hard to meet up to. For example, one assumption is that all independent variables are normally distributed. Ohlson also presented his own prediction models by instead using the statistical method called logistic regression. This method avoids the problems of MDA because it is not based on as strict assumptions (Ohlson, 1980). Nine financial variables were used in the models and these are presented in table 2.1 above. The table shows that Ohlson's model contained variables similar to those Altman used. For example, both models contained a return on assets ratio, a leverage ratio and a working capital ratio. However, Ohlson also included two dummy variables. The first dummy accounted for companies with negative equity capital. According to Ohlson, companies with a negative equity has a considerably higher probability of going bankrupt and it therefore makes sense to include a variable that accounts for this effect. He also included a dummy variable that was set to one for companies that had had a negative net income for the last two years. A problem with the model though is that not all variables were statistically significant. For example the dummy variable that accounted for companies with a negative net income for two years in a row was not significant in one version of the model.

One problem with many accounting-based models, including Altman's Z-score model and Ohlson's model is that they are based on pooled data from many years. Altman's model was estimated using financial data from 20 years, and Ohlson's model used data from seven years. When pooling data the assumption is made that bankruptcy predictability of different combinations of ratios is stationary and does not vary over different economic conditions, and this may not be the case (Mensah, 1984).

2.3.2 Market-Based Models

The market-based models are the other category of credit risk models. What characterizes these models is that they are based on a theoretical foundation of option pricing theory. The Merton model, developed by Merton (1974), is considered the first developed model within this area. His model in turn was based on Black & Scholes (1973) previous work.

In the Merton model, the equity of a company is viewed as a call option on the company's assets (Merton, 1974). The debt of the company is assumed to be a zero-coupon bond with the face value B, maturing at time τ. In the event that the firm value, V is higher than B at the maturity date the debt holders get paid the full face value B and the remaining V_t-B is the equity value that belongs to the shareholders. If $V_t<B$ the firm goes bankrupt and the bondholders receives the liquidation value while the shareholders receives nothing. The principal of the debt B is therefore the default barrier which in option terms can be viewed as the strike price and V can be viewed as the price of the underlying asset. Based on this reasoning, the call option pricing formula can be used:

$$E = VN(d_1) - Be^{-r\tau}N(d_2) \tag{1}$$

Where

$$d_1 = \frac{\ln\left(\frac{V}{B}\right) + \left(r + \frac{\sigma^2}{2}\right)\tau}{\sigma\sqrt{\tau}} \ and \ d_2 = d_1 - \sigma\sqrt{\tau} \tag{2}$$

And where *N(d)* is the cumulative probability of the standard normal density function below *d* (Black & Scholes, 1973). Merton (1974) used the formula to define the value of a company's equity and then used a parity relationship to derive the value of the risky debt.

The theory can also give an estimate of the probability of default. The variable $N(d_2)$ represents the risk-neutral probability that the firm will be solvent at maturity, and correspondingly $1\text{-}N(d_2)$ is the probability that the firm will default (Charitou et al., 2008). Moreover, by substituting the risk-free interest rate to the expected asset return in the formula above, the actual probability of default can be estimated (Gray & Malone, 2008).

However, there are many assumptions behind the Merton model and market-based models in general. One assumption characterizing the original Merton model is that a company can only default if the value of the firm is below the default barrier at the maturity date. This assumption has afterwards been relaxed in different modifications of the model. Black & Cox (1976) for example developed a framework that triggers default as soon as the firm value falls below the default barrier.

A lot of other adaptations to the Merton model have also been made. Vasicek (1977) for example changed the fixed risk-free interest rate in the model to an interest rate that changes stochastically. Collin-Dufresne and Goldstein (2001) on the other hand argued that a capital structure rarely is fixed, and presented a modified model with a capital structure that reverts to the mean.

Another kind of modifications is the ones that let the borrower decide when to default (Charitou et al., 2008). One such modification was made by Anderson et al. (1996). Their starting point was a game theoretic model based on discrete time, previously developed by Anderson and Sundaresan (1996). This model they then developed in a continuous time framework. The argument behind the model is that it can be rational for a firm to default on a loan. The reason is that bankruptcy is a costly process and that it therefore can be rational for the creditor to accept the default and renegotiate the terms rather than liquidating the company.

2.3.3 Hazard Models

In 2001, Shumway published an article where he criticized the traditional accounting-based models for being static. He argued that since they only use observations of companies from a single point in time a lot of information is left out, such as the company's development over time. Also, often such single-point observations from different companies are pooled over many years.

Shumway's solution was a new technique based on a hazard model. This model is a kind of survival model where the dependent variable is the time the firm will stay non-bankrupt. Shumway used corporate data from 30 years and estimated a model where this "health" was a function of firm age and a combination of different market-based and accounting-based variables. He concluded that combining market-based and accounting-based variables increases the accuracy in out-of-sample forecasts.

2.4 Previous Research around Industry Characteristics

Over the years, updated versions of Altman's Z-score model have been published. One version is the Z'-score model that is adapted to privately held firms (Altman, 2000). This model differs in that the market value of equity/book value of debt ratio is substituted to a similar ratio but with only book values. However, a drawback of the model is that the model still is estimated using only financial data from publicly held companies. Another version Altman (2002) presents is the Z''-score model, which is adapted to non-manufacturing firms and firms in emerging markets. This model excludes the ratio sales/total assets because it is a very industry-sensitive ratio according to Altman.

Other researchers have presented bankruptcy prediction models adapted to other industries such as the construction industry (Ng et al., 2011), the hospital industry (Al-Sulaiti & Almwajeh, 2007) and the hotel industry (Kim, 2008). Kim & Gu (2006) studied the restaurant industry in the US and modeled bankruptcy risk using both MDA and logistic regression. The two models contain only two independent financial ratios: total liabilities/total assets, and EBIT/total liabilities. Their study is interesting for two reasons. First, the study showed that the two methods performed equally well. Second, the models had a high out-of-sample prediction accuracy with 93% of all companies correctly classified, despite using only two financial ratios.

One problem with the industry-specific models is that they do not tell anything about differences regarding how the bankruptcy-indicating explanatory power for different financial ratios varies across industries. Even though a comparison can be made between different industry-specific models in the literature, such a comparison would not be very reliable because of differences in financial ratios used and different time periods for the model estimations.

Dakovic et al. (2010) did a study on Norwegian companies and compared different methods to build bankruptcy prediction models. One of their models accounts for industry differences in the intercept by including industry-specific dummy variables. However, their purpose is to see if one can enhance the bankruptcy prediction accuracy by examining the best functional form of different financial ratios and less attention is paid to industrial differences. Since they do not present any numbers on the estimated coefficients it is not possible draw any conclusions on industry differences in their results. Also, since no interaction terms are used to account for differences in the marginal effects of ratios across industries, it would not be possible to draw any conclusions about these differences either.

Platt and Platt (1990) examined the effects of industry-relative ratios on bankruptcy. They used seven financial and operational variables and estimated two models. The first model included the seven ratios and the second model included the same ratios but industry-normalized by divided by the industry average. Industry effects were also incorporated through an industry-wide factor in the second model: Two of the variables included in the model were the product of two other factors. The first of these factors was the percentage change in total output for the industry the company belonged to. The second factor was a cash flow ratio and a leverage ratio respectively. The authors found that the model including industry-relative ratios correctly classified a higher percentage of the sample. They also found that industry effects were significant on corporate failure and that the model including the change in industry-output significantly performed better than the one without this variable.

Chava and Jarrow (2004) take the industry effects analysis one step further. They analyzed industry effects for four selected industries by using interaction terms in a hazard model, presented in table 2.2 below. The four industry categories included in the analysis were the finance, insurance, and real estate industry; the transportation, communications and utilities industry; the manufacturing and minerals industry; and a miscellaneous grouping of the rest of the industries. The authors conclude that it is important to include industry effects in a hazard model since the intercept and slope coefficients are significantly affected by the industry groupings.

They also conclude that the industry effects significantly improve the accuracy of the model. However, a problem with their model is that they use very broad industry groupings and that the fourth industry is a group of many different industries. Since the miscellaneous grouping is used as the reference industry and is not assigned any dummy variable, the other industries are compared to this industry. This makes it hard to interpret the results, since this group consists of many different industries. Another weakness of their model is that it only includes two financial ratios – net income over total assets and total liabilities over total assets. Even though two ratios may be enough to create a good model, it means that the study does not tell anything about how other ratios may differ across industries. A third weakness of their study is that they use data from the time 1962 to 1999, which is a very long time period. Over this time period a lot of things have changed and industries have developed which makes it hard to draw conclusions of industry differences in today's world.

Table 2.2

Coefficient	Variable	Explanation
-5.9090***	Intercept	
-1.0466***	NITA	Net income/total assets
2.2036***	TLTA	Total liabilities/total assets
-0.9619***	IND2	Manufacturing & Minerals
-0.7524*	IND3	Transport & Utilities
-0.8315**	IND4	Finance & Real Estate
-0.2354	NITA*IND2	
0.8275***	TLTA*IND2	
-1.4547***	NITA*IND3	
0.1174	TLTA*IND3	
-2.2822***	NITA*IND4	
-0.5104	TLTA*IND4	

Table 2.2 shows the variables and their coefficients in Chava & Jarrow's (2004) bankruptcy prediction model.

The previous studies show that it may be advantageous to adjust a bankruptcy prediction model to industry differences. However, the only study trying to explain how bankruptcy-indicating abilities of financial variables may vary across industries is the study by Chava and Jarrow (2004). The following study will address the problems that were detected in their study and go deeper into the subject. First of all, financial data from only one year will be used in each model. In this way, only data from the same macroeconomic climate will be used in a model. Furthermore, models will be estimated for six years. This allows comparison over the years and makes it possible to draw conclusions about temporary versus more long-term differences between industries. Finally, a larger number of well-defined industries and a larger amount of data will be analyzed in order to come up with new insights on the subject.

2.5 Evaluation of Prediction Accuracy in the Literature

Within the literature of accounting-based prediction models, the common practice is to end a study by testing the estimated model to evaluate its prediction accuracy. By choosing a cut-off value and applying the model on a sample the model is evaluated based on its ability to classify companies into the two groups failed and non-failed companies. The type I and type II errors are also measured where the type I error is the probability of misclassifying a failed firm while the type II error is the probability of misclassifying a non-failed firm (Beaver, 1966). Beaver used this method in his study and found a prediction accuracy for single ratios of up to 87% one year prior failure. Altman has tested his model in this way too, and has later repeated the test of his model on other samples. His Z-score model has generally performed at 82%-94% classification accuracy (Altman, 2002). Ohlson (1980) also tested his own model, and found an error rate of 14.9%, which implies a prediction accuracy of 85.1%. Other models have been tested too, such as Kim & Gu's (2006) model adapted to the restaurant industry which got an prediction accuracy of 93% on a holdout sample.

However, a problem with some of these evaluations is that they do not use a holdout sample to validate the function but instead the same sample as was used for the model estimation. Ohlson (1980) for example, used the same sample for the model evaluation with the argument that there was not enough data available for a different sample. According to Hair et al. (2010), using the same sample can create an upward bias in the prediction accuracy of the validation. This can make it harder to compare Ohlson's results with others.

Another problem is the different methods and structures used for the evaluations. Altman (1968) and Kim & Gu (2006) for example used two equally sized samples of bankrupt and non-bankrupt companies and a cut-off value that maximized the total number of correct classifications. However, this approach may not be very realistic considering that in the real world there are much more non-bankrupt than bankrupt companies. In a world where for example 5% of all companies will go bankrupt within 1-2 years and 95% will not, a prediction accuracy of 95% would be achieved just by classifying all companies as non-bankrupt. More realistic proportions and a discussion on the tradeoff between misclassifying bankrupt and non-bankrupt companies could therefore make these evaluations better.

2.6 Discussion on Motives for Using Empirical Models

One may ask why so much empirical research is made on bankruptcy modeling when there already exist models based on a theoretical foundation that has been proved to be better in predicting bankruptcy. Hillegeist et al. (2004) for example tested the Altman Z-score model, Ohlson's (1980) model and a version of the Black and Scholes model. They found that the Black and Scholes model performed significantly better than the other two models.

One reason could be actual model usage. According to research by Beaulieu (1996), accounting information is a fundamental component of the loan approval process in banks. Interviews held with representatives at Swedbank during this project have also supported these results. According to Torbjörn Johansson, a credit specialist at the Collections department at Swedbank, accounting data and cash flow analyses are important tools in the loan approval process.

This in turn raises the question why the accounting-based models are preferred by those practitioners. One reason could be the information requirements for the different kinds of models. While the accounting-based models only require accounting data, a hazard model is based on time series of data and the theoretical models are based on market values and their volatility. Time series may be difficult to create depending on information availability and market values can be hard to estimate for private companies since they are not traded publicly.

2.7 Hypothesis

Based on previous studies it is possible to pick out some financial ratios that are likely to fit in a prediction model. Many studies have used a leverage ratio, a profitability measure, and some kind of measure on how much current assets a company possesses.

These variables can also somehow be explained in a theoretical or logical way. Leverage is a fundamental basis in the market-based models. An increased leverage raises the default barrier and increases the probability that the value of the company will be less than this barrier. More debt also increases the cost the company will have to pay each month in interest. This can be a problem for companies that cannot easily go to the capital markets anytime and where liquidity is a scarce resource. A profitability measure is also a reasonable indicator on bankruptcy. A high return on assets normally indicates that a company generates cash, which is essential for a company’s long-term survival. The profitability is also represented in the market-based models through the asset-growth variable. Lastly, liquidity is a reasonable indicator on bankruptcy, at least in a short perspective. As was discussed earlier, illiquidity is a common reason for company default. This can be motivated from the regulatory framework presented above. Since a creditor can force a company into bankruptcy if it does not meet a financial obligation within six months, it is always important for a company to have access to liquid assets. A company with limited access to liquid assets should therefore be more likely to go bankrupt, at least in a six month perspective.

It is harder to motivate a hypothesis regarding industry differences and the effect of including these in a bankruptcy prediction model. However, the study by Chava & Jarrow (2004) can give some insights of what to expect. Their study shows that there might be at least some industry differences to expect. More specifically, one hypothesis that can be formulated based on their study is that the manufacturing industry is more sensitive to changes in leverage than the transportation and utilities industry. Another hypothesis that can be formulated is that the transportation and utilities industry is more sensitive to changes in net income over total assets than the manufacturing industry.

Regarding prediction accuracy, a classification accuracy of 82-94% can at least be expected, since this is the accuracy of Altman’s Z-score model (Altman, 2002). However, since Chava & Jarrow (2004) concluded that their model with industry effects increased the accuracy, there is a chance that the prediction accuracy may be higher even in this study.

3 METHODOLOGY

This section presents the methods used in this study. The purpose is to provide the reader with an understanding of how data has been collected and analyzed in order to get the results.

3.1 Choice of Statistical Model

In this study, logistic regression was chosen as the modeling framework. The method was chosen because of its statistical properties and its similarities to multiple regression. An alternative method would have been multiple discriminant analysis (MDA) which has frequently been used within the bankruptcy prediction field (e.g. Altman (1968) and Deakin (1972)). However, according to Eisenbeis (1977) a lot of business and finance research using MDA suffer from methodological and statistical problems. Two of the problems relates to the underlying statistical assumptions. First, MDA is built on the assumption that the variables being used to describe the groups are multivariate normally distributed. Second, the groups being investigated are assumed to have equal variance-covariance matrices.

Logistic regression on the other hand does not rely on these strict statistical assumptions and is a much more robust technique. It is a binary model, modeling a dependent variable with two possible values: 1 and 0. The values can represent groups or events and will in this study represent bankrupt (=1) and non-bankrupt (=0) firms. The model has many similarities to multiple regression and has the following form:

$$\ln\left(\frac{p_{event}}{1-p_{event}}\right) = b_0 + b_1x_1 + \cdots + b_nx_n \tag{3}$$

Where $p_{event}/(1-p_{event})$ is called the odds ratio, p_{event} is the probability of an observation belonging to group 1, b_n are regression coefficients and x_n are independent variables. In contrast to multivariate linear regression, the model is not estimated using ordinary least squares (OLS). Instead, the logistic regression model is estimated using another estimation technique called Maximum Likelihood. While OLS minimizes the squared error terms, the maximum likelihood method finds the most likely estimates of the regression coefficients in an iterative process. (Hair et al., 2010)

The fact that the dependent variable in this formula contains an estimation of the probability of a group belonging is an interesting feature considering the modeling purpose of this study. If close-to-bankruptcy firms are coded 1 and non-bankrupt firms are coded 0, the output of the model can be interpreted as a probability of bankruptcy estimation.

However, one property of the logistic regression model that makes it difficult to interpret is the form of the regression coefficients. In an ordinary multiple regression model the coefficients can be interpreted as the change in the dependent variable that will be caused by a one unit increase in the independent variable. In the logistic regression on the other hand this interpretation is not as simple. As the formula above shows, a regression coefficient reflects changes in the log of the odds ratio. By exponentiating the coefficients however, the coefficients can be interpreted as the change in the odds ratio when the independent variable changes (Hair et al., 2010).

To incorporate industry effects into the logistic regression model, interaction terms were chosen to be used. Interaction terms are cross-partial derivatives or differences that account for the difference in marginal effect that an independent variable has on a dependent variable depending on another independent variable (Karaca-Manic et al., 2012).

The logistic regression function with incorporated interaction terms has the following formula:

$$\ln\left(\frac{p_{event}}{1-p_{event}}\right) = b_0 + b_1x_1 + b_2d_1 + b_3x_1d_1 + \cdots + b_nx_i + b_{n+1}d_j + b_{n+2}x_id_j \qquad (4)$$

Where b_n are regression coefficients, x_n are financial variables and d_n are industry-specific dummies that equals 1 for the specific industry and 0 for all other industries. If *j+1* industries are chosen to be studied then there will be *j* industry-specific dummy variables. One industry will have no dummy variable and will be a reference industry that the other industries are compared to.

There are two specific terms for each industry except the reference industry. The first term has the form b_nd_j and is an adjustment in the intercept for the industry. By adding this industry-adjustment to the constant b_0 in the model, the sum b_0+b_n equals the total industry-specific intercept. An exponentiated form of the intercept ($exp(b_0)/(1+exp(b_0))$) equals the estimated bankruptcy probability for an observation where all other included variables equals zero. The industry-specific dummy terms can therefore catch such possible differences that could exist across industries.

The second kind of industry-specific term has the form $b_n x_i d_j$. This term adjusts for the different effect a change in x_i can have on $ln(p_{event}/(1-p_{event}))$ depending on industry. The total effect that a financial variable has on $ln(p_{event}/(1-p_{event}))$ for a specific industry is here calculated by adding the industry adjustment term $b_n x_i d_j$ to the unadjusted term $b_{n2} x_i$. Since $d_j=1$, the industry-specific coefficient is equal to b_n+b_{n2}, the sum of the coefficients for the two terms respectively.

All interaction terms may not be significant in an analysis. However, according to Brambor et al. (2006) all constitutive terms should be included in a regression model with interaction terms. Thus, even though some terms will not be significant, all combinations of $b_n x_i$, $b_n d_j$ and $b_n x_i d_j$ will be included in the model.

3.2 Data Collection

To be able to estimate the logistic regression models, a sample of observations and their respective values on a number of financial ratios were needed.

3.2.1 Data Sample

The original sample of observations was downloaded into Microsoft Excel using the export tool from the online data base Retriever. 419,269 annual reports were downloaded, covering approximately 80,000 companies over the six year period 2006 to 2011. From the data sample, around 50,000 annual reports for companies with less than five employees at the time of the report were deleted. According to Ohlson (1980), financial companies differ systematically from other companies and should not be included in a bankruptcy prediction model. Therefore, around 10,000 annual reports from companies within this sector were also deleted. Finally, a number of financial reports from before 2006 and a number of doubles were deleted. The final sample contained of 317,187 annual reports of non-financial, privately held corporations from the time period 2006 to 2011.

To be able to test the estimated models, each annual sample were split into two equally sized subsamples. The first subsamples contained corporate data used to estimate the regression models. These samples will be called “the estimation samples” throughout this paper. The second subsamples contained corporate data that was used to test and validate the estimated models and are called “the holdout samples”. According to Hair et al. (2010), using a holdout sample is a good way to validate the estimated function and make sure it performs well when applied on another sample. However, there are also drawbacks with the method. Tan et al. (2005) point out a few weaknesses. First of all, having a holdout sample reduces the estimation sample. Second, since an original sample is split into two, the two samples will not be independent of each other. A group that is overrepresented in one of the samples will be underrepresented in the other.

Since the sample sizes were so large, the decision was made to use holdout samples. The gain in being able to validate the estimated models on an external sample was considered larger than the loss in sample size and quality.

One reason for estimating models on an annual basis was to avoid pooling data from different years. According to Mensah (1984), bankruptcy prediction models may not be stationary over time. This was also the reason for why company data from the same year was used to test the prediction accuracy of the model. One weakness of this methodological choice is that it may not be an available option for practitioners. For them, it is not relevant to estimate and use the model on company data from the same time period since the model estimation only can be done when the financial data is a few years old and it is known which companies went bankrupt. However, since the purpose of this study is to assess the opportunity to include industry effects in a bankruptcy prediction model it is reasonable to exclude the effects that using different time periods for model estimation and testing might have.

Estimating models for 2006 to 2011 gives an opportunity to find out how ratios and industry differences vary over time. As was mentioned earlier, Mensah (1984) argue that bankruptcy prediction models vary over different macroeconomic environments. The number of bankruptcies and companies with financial problems does also vary over time. According to Jens Skaring, head of the Financial Restructuring and Recovery department at Swedbank, their workload has increased a lot during recessions in the economy (personal communication, 2013-03-06).

One problem that arose in the data collection process was the inability to export information about company status. Companies were divided into active and inactive companies and this information was possible to export, but not information about corporate bankruptcies. Some of the active companies had filed for bankruptcy but not ended the process and become inactive, and some of the inactive companies had filed for bankruptcy while others had become voluntarily liquidated for example. To solve this problem, a Visual Basics for Applications (VBA) script was composed in Excel. This script searched for all the companies in the data base and downloaded their status into Excel. Even though this script worked automatically this was an extensive computer process working for over 40 hours.

Another problem that arose was that a number of companies were missing industry classifications. In total, around 5000 observations were missing such a classification. Of these, 2276 were bankrupt companies, representing 43% of the total sample of bankrupt companies. To solve this problem, another script was composed. This script searched through the whole sample of company names and looked for indications of industry belonging. For example, a company whose name contained the word “restaurant” was classified as belonging to the hotel and restaurant industry. Other words that the script looked for (most of them in Swedish) were for example “building”, “retail”, “shop” and “transport”.

As mentioned above, 317,187 annual reports were analyzed of which 5,257 were annual reports for companies that later became bankrupt. This total sample represented all available annual reports for non-bankrupt companies and all annual reports for bankrupt companies one report prior bankruptcy, given the population restrictions made above of only using privately held Swedish companies with at least five employees. This means that all available observations were used, except the observations of bankrupt firms before their last annual report. The reason for leaving these observations out of the sample was to make the information-collection process less complicated. The reason for picking all other available company observations was to enable modeling the industry effects.

The downloaded annual reports included financial information from the income statements and balance sheets, and financial ratios. They also contained other company information such as industry belonging. The income statements and balance sheets were used to check the accuracy of the financial ratios but then the downloaded financial ratios were used in the data analysis.

3.2.2 Original Sample of Financial Ratios

To be able to estimate the logistic regression models, a sample of observations and their respective values on a number of financial ratios were needed. 22 financial ratios were provided by Retriever and was the starting point for this analysis. The 22 financial ratios provided were all recommended in the BAS framework. The BAS framework represents the standard of ratios that are used by professionals such as accountants and business managers in Sweden and has become regarded as the standard for financial ratios (Vinell, 2011). The framework contains in total 67 ratios of which 16 ratios are classified as standard financial ratios and 51 are supplementary ratios (BAS, 2010). The 22 ratios downloaded from Retriever were matched with the ratios in the framework for accurate definitions and categorizations and are presented in table 1.1 in exhibit 1. Of all the downloaded ratios 12 were categorized as standard variables and 10 as supplementary. To ensure validity in the financial ratios a selected sample of ratio numbers were checked randomly for accuracy in accordance to the BAS framework. This was done by calculating the ratios manually, using the downloaded financial statements.

In combination with the ratios provided by Retriever and BAS, a few ratios were added because of their appearance in the literature. Working capital/total assets and log(total assets) are examples of such ratios, added because of their presence in Ohlson's (1980) study. These are also presented in exhibit 1 and are listed in the most suitable categories.

Some financial variables were later excluded, such as interest coverage, interest on debt, risk margin and operating risk margin. This was done largely due to that one application of the models could be for financial institutions to assess the level of interest a company should pay on its debt. Including the interest rate in the model would then result in a circular argument where the risk assessment would be based on the interest rate which in turn would be based on the risk assessment.

3.3 Data Analysis

After the data was collected it had to be analyzed before it could be modeled. In this process a better understanding of the data was achieved and irrelevant data could be excluded.

3.3.1 Basic Analysis of the Data and Choice of Industries

Before analyzing the data in Eviews discrepancies in the sample downloaded from Retriever were adjusted for. In the data sample some financial ratios had been distorted due to that Retriever had used incorrect numbers when calculating ratios which resulted in extreme values for some variables. These observations were easily found and deleted. Further regards were taken to the financial variables through a filter in Eviews that sorted out any companies with zero or negative total assets. This was done since many variables are in relation to total assets and thus would affect the variables analyzed in a misguiding fashion. The sample was structured after industry classification, year and with corresponding companies that were bankrupt and non-bankrupt. Due to the vast amount of companies included in this study it would be too time consuming to manually inspect and categorize every company to its respective industry. Therefore there are a portion of the companies which does not have any industry classification.

The five industries chosen for the study were the building and decoration industry; the hotel and restaurant industry; the manufacturing industry; the retail industry; and the transportation industry. The criterion that was used for selection of the five industries was the number of bankrupt observations within each industry. The industries chosen were those with the highest number of bankruptcies over the time period 2006-2011. There were mainly two reasons for choosing these industries. First, choosing the most representative industries makes the models applicable to many companies. Second, the large sample size of choosing the most bankruptcy-representative industries makes it easier to model industry effects. A drawback of choosing the most representative industries though is that it might not be the most dissimilar industries. One can argue that this would have been a better criterion for the study. The problem of using dissimilarity as the criterion for choice of industries though would be to find a method to measure dissimilarity. One could look at averages of different financial ratios across the industries for example but then one would also have to find a way to put weights on the different ratios and to combine them into one measure. No such attempts were made in this study.

The number of industries examined was reduced to five for several reasons. First of all, if every industry is included (28 industries) and four financial variables are analyzed, the model would contain 27*5=110 interaction terms which would make the result unnecessarily complex. Second, some industry samples were too small to provide valuable information such as the hair and beauty sector; the consumer services sector; and the sewer, waste, electricity and water sector, which only had 10, 11 and 5 cases of bankruptcies respectively.

3.3.2 Univariate Analysis and Analysis of Correlations

In order to reduce the large number of financial ratios collected from each company, a univariate analysis was performed. According to Nina Larsson, a credit risk modeler at Swedbank, a univariate analysis is a good procedure to reduce the number of variables before start modeling. Some kind of univariate analysis (sometimes called *profile analysis*) is also a common practice in the literature, performed by for example Deakin (1972), Ohlson (1980), and Skogsvik (1990).

In this analysis, the non-equality in mean values between the group of bankrupt and non-bankrupt observations were tested for its significance. The groups consisted of all bankrupt and non-bankrupt company observations that belonged to the five industries selected earlier, regardless the years they belonged to. So called t-tests were performed and only financial ratios with a significant difference between the mean values of the groups were further analyzed. In this analysis, 17 financial ratios passed the tests. The results from the tests are presented in section 4.2.1.

There are a few weaknesses in the choice of methodology in this analysis. Since more than one annual report was collected from most of the companies, all observations will not be completely independent in the pooled sample. Independence between the observations is however a fundamental characteristic of a random sample. A random sample in turn is necessary to make statistical inference (Körner & Wahlgren, 2009). This violation of these assumptions was not considered so dramatic though since the samples are so large. Although most observations are related to a few other observations they are independent to *almost* all other observations.

Another weakness is that the evaluation of mean values between bankrupt and non-bankrupt companies does not necessarily tell the predictive ability of a ratio. A ratio may not be a good predictor of bankruptcy just because a statistically significant difference in the mean values is found. If the dispersion around the mean values is wide and the distributions of the two groups are overlapping, this would indicate a lower degree of predictive ability (Beaver, 1966). However, the univariate analysis was considered a good method for an initial screening where ratios with a potential good predictive ability could be filtered out.

In a last step before starting the modeling, the correlations between the different variables left were analyzed. The purpose of this study was to check for any unexpected relationships between the variables that could cause multicollinearity (Hair et al., 2010).

3.3.3 The Final Modeling

After the univariate analysis was finished a sample of financial ratios were ready to be tested in the model estimation process. In the primary tests all variables that proved significant in the univariate test was put into the model for bankruptcy prediction. Then insignificant variables were removed step-by-step in a backward elimination process. This removal was based on the insignificance of variable coefficients but considerations were also taken to the ratio categorization in the BAS framework explained earlier and to the analysis of correlations. Multiple variables from the same category, measuring more or less the same thing were avoided in the final model. Since the models were estimated on an annual basis, six models were estimated, covering the time period 2006 to 2011. This approach created additional problems since the models were supposed to be comparable containing the same variables. Variables were looked for that showed significance over all the years. The final model however contained one ration (return on total assets) that was insignificant in one year on the 5% level of significance.

The methodology used to estimate the models with industry effects was more straightforward. Since the models with industry effects were supposed to be comparable with the models without industry effects, they had to contain the same financial variables. In addition to those, interaction terms and dummy variables were added for all of the industries except the manufacturing industry which was chosen as the reference industry. The interaction terms were added for all combinations of financial ratios and industries even though many of them were insignificant. The reason was to make it possible to compare all industries and ratios, also over the years.

3.4 Finding the Optimal Cut-Off Values

To find a cut-off level optimal for separating bankrupt and non-bankrupt companies, an ROC analysis was performed in the statistical computer program IBM SPSS. The ROC analysis is a way of visualizing, organizing, and selecting classifiers based on their performance (Fawcett, 2006). It illustrates the tradeoff between accurate positive classifications and accurate negative classifications and can be used to find an optimal cut-off score.

Before the ROC analysis started the logistic regression models were applied on the estimation samples. Using the models, probability-of-bankruptcy values were calculated for each observation.

The ROC analysis was then used to analyze how the distribution between the four following categories changed depending on cut-off value. The four categories are defined as follows:

1. If a company is bankrupt and it is classified as such it is a *true positive.*
2. If a company is bankrupt and classified as non-bankrupt it is a *false negative.*
3. If a company is not bankrupt and classified as such it is a *true negative.*
4. If a company is not bankrupt and classified as bankrupt it is a *false positive.*

The optimal cut-off value is based on the tradeoff between sensitivity and specificity. The sensitivity measures the true positive-rate (tp-rate) which in this case is the amount of actual bankrupt companies that have been classified as such in relation to the total amount of companies that have been classified as bankrupt.

$$Sensitivity\ (True\ Positive\ rate) = \frac{true\ positive}{true\ positive + false\ negative} \tag{4}$$

Specificity in turn represents the number of actual non-bankrupt companies that are classified as non-bankrupt companies in relation to all companies classified as non-bankrupt.

$$Specificity\ (1 - False\ positive\ rate) = \frac{true\ negative}{true\ negative + false\ positive} \tag{5}$$

The results are then plotted in a two-dimensional graph with the sensitivity (true-positive rate) on the Y-axis and 1-specificity (false-positive rate) on the X-axis (Pendharkar, 2011). The results from this study are presented in section 4.5.

The more the curve bends towards the upper left corner, the better. This is so because the upper left corner represents a situation where both a high sensitivity and high specificity is achieved. This in turn is desired since it depicts a higher number of correctly classified observations. If all observations are correctly classified there will be 100% sensitivity and 100% specificity.

Through the diagram, a diagonal line is drawn that represent the outcome of randomly guessing the group belongings. Any point above this diagonal line has a higher accurate classification ratio and it is thus implied that some information in the data sample is exploited to generate these results. Any point under the diagonal line is also of interest, not because it adds any added accuracy but because a classifier that yields these results performs worse than random guessing. The area under the curve can be used as a measure of the ability of the model to correctly classify observations into the two groups (Fawcett, 2006).

However, the ROC diagrams discussed above only show the tradeoff between sensitivity and specificity. They do not however tell which the optimal cut-off value is. This depends on the importance of high sensitivity versus high specificity. In this study, equal weight was put on sensitivity and specificity. Therefore, cut-off values were chosen where sensitivity and specificity were equally high. To find the optimal cut-off value, the sensitivity and specificity for different cut-off values were plotted. At the point where they intercept the optimal cut-off value was found.

This criterion used to find the optimal cut-off values in this study might not be the optimal cut-off values for other stakeholders using the models though. To find the optimal cut-off values the user would have to first evaluate the costs and benefits of misclassifying and correctly classifying bankrupt and non-bankrupt companies. If the cost of misclassifying a bankrupt company as non-bankrupt is very high compared to the cost of misclassifying a non-bankrupt company as bankrupt, then the cut-off value should be low. However if the opposite situation is present, then the cut-off value should be higher.

3.5 Evaluating the Classifying Abilities of the Models

The last step in the analysis was to examine how well the estimated models could classify companies as bankrupt and non-bankrupt. According to Han and Kamber (2006), ROC curves are a good tool for comparing two classification models. Therefore, this method was chosen as the first way of evaluating the models. By comparing the areas under the curves for the models with and without industry effects and using statistical tests of equality, differences could be found.

The ROC analysis was done on both the estimation sample and the holdout sample, where the holdout sample was used to validate the results. The results from this analysis are presented in section 4.5.

In the literature, a common way of evaluating a bankruptcy-prediction model is to calculate the prediction accuracy by using a cut-off value. Such an evaluation was also done in this study as a second way of evaluation. The cut-off values that earlier had been estimated in the ROC analysis were used, and the models were tested on both the estimation samples and the holdout samples. The results from this analysis are presented in section 4.6. In this analysis, the actual sensitivity, specificity and prediction accuracy for the different models could be found. To evaluate the differences between the models with and without industry effects, tests of equality were performed in this analysis too. As was argued before, sensitivity and specificity were considered equally important and cut-off values were chosen where this was achieved. Testing the equality of the prediction accuracy between the models would therefore not be right since the prediction accuracy is a *weighted* average of the two measures. Instead, a fourth measure was calculated, defined as the *mean* of the sensitivity and specificity. In this measure, sensitivity and specificity were equally important. The statistical tests were then performed to test the equality of this measure between the two kinds of models.

3.6 Methodological Discussion

According to Bryman and Bell (2005), reliability and validity are two criteria for evaluating business research. The reliability of a study reflects the possibility to repeat the study with the same outcome. If the outcome is not affected by different conditions it is a study with a high reliability. Validity on the other hand is about using measures that measure what the study intend to measure (Bryman & Bell, 2005).

To ensure reliability, a number of actions were taken. First of all, only well-established statistical methods recommended by Hair et al. (2010) were used. The quantitative data that was used was collected from the data base Retriever. This data base collects the information from well-recognized sources such as the Swedish Companies Registration Office, the Swedish Central Bureau of Statistics and the Swedish Tax Agency (Retriever User guide). However, the data sample that was downloaded was not at the beginning flawless. The program Retriever had in some instances confused the number of employees with the number of board members which lead to some extreme values for financial ratios such as profit or cost per employee. These extreme values was easily spotted and corrected. For all financial variables a check was made so that similar problems did not occur. Since it is not possible to manually check around three hundred thousand annual reports it is still possible that some variables were not calculated correctly. In order to minimize this risk a sample of random checks was made on the data after adjustments was made.

According to Bryman and Bell (2005), there are three types of validity relevant to this study: construct validity, internal validity, and external validity. One action taken to ensure construct-validity was by using only well-established financial ratios recommended by the BAS Accounting Group and previous studies. BAS' (2010) categorization and explanation of the ratios further improved the validity of this study by giving an understanding of what the ratios are measuring.

Internal validity is about making conclusions about causality that are reasonable (Bryman & Bell, 2005). Is X causing Y, or are there some other relationship? In bankruptcy modeling, causality relationships are not very important. Whether a financial situation is causing bankruptcy or not does not matter when the purpose is only to build a bankruptcy prediction model. Since the purpose is *not* to explain *why* a company goes bankrupt but only to predict the likelihood of bankruptcy, what matters is only how well a variable can indicate bankruptcy. However, as mention previously a few variables were excluded in the analysis due to their intricate relationship to the interest rate. This action was taken to keep a high internal validity and avoid a circular argument.

External validity on the other hand is how well the results from a study can be generalized (Bryman & Bell, 2005). One action taken to evaluate the external validity was to test the models on a holdout sample. Since most of the population of annual reports from the time period 2006-2011 has been used, the external validity can be assumed to be high. However, only a short time period has been studied, and generalizing over other time periods may not be as good because of e.g. macroeconomic conditions.

One other possible fault in the data sample is that many companies that were downloaded did not have an industry classification. This in itself is not a problem due to the size of the sample but the misrepresentation of the ratio of bankrupt versus non-bankrupt companies affects the models ability to depict reality. Table 2.1 in exhibit 2 shows the bankruptcies across industries, and here it is obvious that the ratio of bankrupt companies in the uncategorized group is significantly higher compared to the same ratio for the group of companies *with* an industry classification. In total there are 5257 bankrupt companies of which one third lacks industry classification. This portion represents 40% of the total number of non-classified companies. One reason for this could be that many companies that go bankrupt do not provide a lot of information in their annual report which could imply that they are small companies. Another likely explanation to why there is a distortion of bankrupt companies in the uncategorized sample could be that the data base Retriever fail to collect or save this information for bankrupt companies.

4 EMPIRICAL RESULTS

This chapter presents the results that were obtained from the study. First a section about descriptive statistics is presented, followed by results from the analysis of ratios. Thereafter, models excluding and including industry effects are presented. Finally, the results from the different accuracy tests are presented.

4.1 Presentation of Descriptive Statistics

Table 2.1 in exhibit 2 shows the full range of industries that were downloaded from Retriever. The table shows for each year the number of companies in each industry that went bankrupt in relation to the number of companies in their respective industry that did not go bankrupt. The most interesting observation that can be made from this table is that the amount of bankrupt companies is significantly higher for those companies that lack an industry classification in the data.

Other information this table provides is that some industries have a higher frequency of bankruptcies than others. For example the travel agencies and tourism sector; staffing and employment agency sector; and real estate sector have more than twice as high percentage of bankrupt companies than the sample as whole. On the other side of the scale we have the sewer, waste, electricity and water sector; the legal, business and consulting services sector; and the wholesale sector. As mention previously the choice of industries to include in the model depended on the sample size of bankrupt companies which also becomes clear in the table.

4.2 Results from Analysis of Ratios

4.2.1 Univariate Analysis

Table 3.1 in exhibit 3 shows the results from the univariate analysis where the equality in mean values between bankrupt and non-bankrupt companies for the different financial ratios was tested. The table shows that the null hypothesis of equality was rejected for 17 of the variables at the 5% level of significance which means that there is a statistically significant difference between bankrupt and non-bankrupt companies in these cases.

The variables that did not pass the test were CHSA, INVSA, INVTO, R_OPC and RECSA. These variables were therefore omitted from the further analysis.

The differences between bankrupt and non-bankrupt companies are in line with the expectations. Previous studies in combination with common sense would suggest that the relationships should be as follows:

Table 4.1

Positive	**Negative**		**Indeterminate**
LEV	CAPTO	PRMG	CEMPL
STDSA	CHSA	R_E	INVSA
	LIQSA	R_OPC	INVTO
	LIQSTD	R_TA	RECSA
	LIQTA	SAEMPL	
	LOGTA	SOLID	
	OPMG	WCAPSA	
	OPPREMPL	WCAPTA	

The expected relationships between each variable and the probability of bankruptcy

Clearly, the results show that most of the variables differ as expected. The only significant difference that contradicts the expectations is the CAPTO (capital turnover) ratio. This variable was expected to be lower on average for bankrupt companies. This was an expectation supported by previous research by Altman (1968) where he found a negative relationship between the capital turnover and bankruptcy. However this ratio was not statistically significant in Altman's analysis and was largely included due to its relationship to his second most significant variable that was retained earnings/total assets.

4.2.2 Industry Differences

Table 4.1 in exhibit 4 shows the mean of the financial variables for the five selected industries. The table provides an overview of the differences between the industries in regards to their financial variables and how the variables differ between non-bankrupt and bankrupt firms within and across industries. As was discussed above, CAPTO is higher for companies close to bankruptcy than for non-bankrupt companies. What is interesting in this table is that this unexpected difference is visible over all industries and not only for the total sample. In the table it also becomes clear that a number of other variables also differ across the industries. For example it can be seen that LEV (leverage) is higher for the hotel and restaurant industry than for the manufacturing industry for both non-bankrupt and bankrupt firms. The hotel and restaurant industry is also the industry with the largest difference in LEV between non-bankrupt and bankrupt companies. Looking at the R_TA ratio, even here the hotel and restaurant industry stands out. This industry is here the one with the lowest values for both bankrupt and non-bankrupt companies. It is also the industry with the largest difference between bankrupt and non-bankrupt companies. One reason why the R_TA is lower for this industry could be that it is an industry with less systematic risk which leads to owners requiring less return.

Looking at the OPMG and PRMG ratios, the building and transport industries are the industries with the smallest differences. The largest differences between bankrupt and non-bankrupt companies for these ratios are instead within the manufacturing industry. Not surprisingly the size of the company (LOGTA) does also seem to impact the likelihood of bankruptcy. Companies going into bankruptcy are on average smaller than the non-bankrupt ones. The table also shows that manufacturing companies on average are larger than all the other industries. It is however harder to draw any conclusions here regarding differences between bankrupt and non-bankrupt companies across industries.

4.2.3 Correlations

The last step before building the actual models was to analyze the correlations among the financial ratios. The purpose of this analysis was to find potential unexpected correlations that would have to be considered in the final modeling.

Table 5.1 in exhibit 5 shows the correlations across the ratios. The table shows that most of the variables are only slightly correlated with the other variables. There are a few pairs of variables that are highly correlated however. Most of them are different capital structure ratios that measure more or less the same thing. LEV and SOLID are for example 99% correlated. The reason for this is that both are different measures of the relationship between equity and debt in a firm’s capital structure. The reason why the correlation is not 100% though is that the SOLID ratio uses an equity measure adjusted for untaxed reserves while no such adjustments are made in the LEV ratio.

The correlation matrix provided a further understanding of the relationships between the different variables. This was then used in the model estimation process. By avoiding using highly correlated variables in the same model, multicollinearity was avoided.

4.3 Models without Industry Effects

Table 6.1 in exhibit 6 presents the estimated bankruptcy prediction models without industry effects. The table shows the estimated coefficients for the intercept and all variables. The table also shows the standard errors for the coefficients and their Z-statistics and probability of not being equal to zero.

Looking at the coefficients, they differ between the years but show a consequent sign. For example, leverage (LEV) shows a positive sign each year, indicating that a higher leverage is correlated with a higher risk of bankruptcy. The signs are also those that could be expected after the univariate analysis. The liquidity ratio (LIQTA), the return on assets (R_TA) and the size measure (LOGTA) all have a negative sign which indicates that a low value is correlated with a higher bankruptcy risk.

All of the coefficients in the models are significant on the 5% level except the coefficient for the return on total assets (R_TA) in 2006. This year, the coefficient has a p-value of 13%.

The size of the regression coefficients gives information about the effect the variables have on the dependent variable. A large coefficient means that a small change in the independent variable has a large effect on the dependent variable $ln(p_{event}/(1-p_{event}))$. From the estimated models, it is clear that the liquidity ratio (LIQTA) has the highest coefficient, followed by the return on total assets ratio (R_TA). This means that a one unit change in LIQTA indicates a larger change in bankruptcy risk than a one unit change in R_TA. However, a one unit change has different implications for different ratios. Both LIQTA and R_TA are measured in percent, where 1% is expressed as 0.01. R_TA is a more diverse ratio than LIQTA though. R_TA has an average difference between bankrupt and non-bankrupt companies of 0.27 while LIQTA only has an average difference of 0.11. 1% is therefore a relatively smaller change for the R_TA ratio than for the LIQTA ratio.

Considering the size of the independent variables and the size of a reasonable change, it is instead the firm size measure LOGTA that seems to be the strongest indicator. Over the six models, this ratio has an average coefficient of -0.56. This is very low compared to the LIQTA coefficient and is also lower than the R_TA coefficient. However, when the size of the measure is considered, it suddenly seems like the greatest indicator of bankruptcy. While LIQTA and R_TA are measured in percent, LOGTA is the natural logarithm of the total assets measured in thousands of Swedish Crowns. This leads to higher values for the LOGTA variable. While LIQTA and R_TA have average differences between bankrupt and non-bankrupt companies of 0.11 and 0.27 respectively, the average difference for LOGTA is 1.2. A change of 1.2 in the LOGTA variable would lead to a change in $ln(p_{event}/(1-p_{event}))$ of 1.2*(-0.74475)=-0.8937, while the corresponding change in the LIQTA variable would lead to a change in $ln(p_{event}/(1-p_{event}))$ of 0.11*(-4.26092)=-0.4687. Clearly, the average change in LOGTA for a company going from non-bankrupt to bankrupt causes a larger change in the dependent variable when holding all other variables fixed.

Table 6.2 in exhibit 6 shows the test statistics for the models. The first one is the LR Statistic, which is a likelihood ratio test that assesses the overall significance of the model. In this test, the null hypothesis is that all coefficients are zero (Eviews User Guide, 2010). The table shows that the test statistic varies between the years but has a p-value of 0.0000 for all years under the chi-square distribution. Therefore it can be concluded that the models have an overall significance.

The table also shows the SEE and McFadden R-square for the models. The SEE is the Standard Error of Estimate and is a measure of how much the error terms deviate from the estimated regression curve. A low value is therefore preferred. As the table shows, the SEE varies between the models within the interval 0.09 to 0.13. The McFadden R-square is also a measure of goodness of fit. It explains how well the regression line approximates the data points in the sample. It always lies between zero and one, where one is a perfect fit (Eviews User Guide, 2010). The six models without industry effects estimated in this study have a McFadden R-square between 0.09 and 0.18.

Table 6.3 in exhibit 6 provides a comparison between the estimated models for 2006 and 2011. Here, the equality between the estimated coefficients for the two years has been tested using the following formula:

$$Z = \frac{(\bar{X}_{2006} - \bar{X}_{2011}) - d_0}{\sqrt{\left(\frac{s_{2006}}{\sqrt{n_{2006}}}\right)^2 + \left(\frac{s_{2011}}{\sqrt{n_{2011}}}\right)^2}} \tag{6}$$

Where Z is the calculated Z-statistic; $\bar{X}_{2006}$and $\bar{X}_{2011}$ are the two mean values that are tested for equality (the regression coefficients in this case); d_0 is the null hypothesis (0 in this case); and $\frac{s_{2006}}{\sqrt{n_{2006}}}$ and $\frac{s_{2011}}{\sqrt{n_{2011}}}$ are the estimated standard errors for the two samples (Körner & Wahlgren, 2009). The corresponding probability value for each Z-statistic is obtained from the cumulative normal distribution function.

The table shows that the null hypothesis of equality is rejected in the test on the LEV coefficients and LOGTA coefficients. The LEV coefficient is statistically lower in 2011, indicating that its effect on the bankruptcy risk has decreased between the two years. In the same way the LOGTA coefficient has also decreased, indicating that size in 2011 to a lower degree can explain bankruptcy than in 2006. Looking over all of the years, these two variables also show a decreasing trend in the coefficients. The LIQTA and R_TA coefficients on the other hand have no significant difference between the years and therefore no conclusions can be made.

4.4 Models with Industry Effects

Table 7.1 in exhibit 7 shows the estimated models including interaction terms accounting for industry differences. The models contain the same four financial variables that were included in the previously presented models without industry effects. The models also contain 20 terms that account for industry differences in the variable coefficients and the intercept constant.

There are much more insignificant coefficients in these models compared to the ones without industry effects. Only 5-13 coefficients are significant in each model at a 5% level of significance. However, almost all interaction terms were significant in at least one of the models and for comparison reasons no terms were therefore omitted.

Table 8.1-8.5 in exhibit 8 shows the total marginal effects that the financial variables have on bankruptcy depending on industry. As was explained earlier, the total marginal effect of a variable x_i for a specific industry is the sum of the coefficients b_n and b_{n2} from the terms $b_n x_i d_j$ and $b_{n2} x_i$. In the table, these marginal effects have been calculated for each variable, industry, and year. According to Yip and Tsang (2007), the significance of the sum of these coefficients (the total marginal effect) can be tested using a coefficient restriction test or equality test. A Z-test was chosen to be employed to evaluate this significance since this test was employed by Eviews when testing the significance of the original regression variables. To be able to use this test, the standard errors of all marginal effects were calculated using the following formula:

$$\hat{\sigma}_{\frac{\partial Y}{\partial X}} = \sqrt{var(b_1) + d^2 \times var(b_3) + 2d \times cov(b_1 b_3)} \tag{7}$$

Where b_1 is the coefficient in the $b_n x_i$ term, b_3 is the coefficient in the $b_n x_i d_j$ term, and d is the dummy variable that equals one for the specific industry (Brambor et al., 2006).

With the estimated marginal effects and standard errors ready, the marginal effects were tested for its significance. A Z-statistic and p-value were obtained for each marginal effect and these are presented in the same tables.

When analyzing the tables, it is clear that different financial ratios are good predictors of bankruptcy depending on industry. For example, R_TA has a significant marginal effect on bankruptcy within the manufacturing industry for most of the years but is insignificant in all of the models for the building industry, hotel and restaurant industry and transportation industry. In the same way, LEV is a very good predictor within the transportation industry and manufacturing industry, but is a little less significant for the hotel and restaurant industry.

Looking at the magnitude of the marginal effects, it is clear that they differ across industries. The LEV ratio has the highest marginal effect on bankruptcy for transportation companies while the effect among hotel and restaurant companies is around zero and most often insignificant. These two industries were also the ones with most significant LEV interaction terms. The transportation industry had positive coefficients that increased the effect compared to the manufacturing (reference) industry, and the hotel and restaurant industry had negative coefficients that reduced the effect from the b*LEV term and which were significant in four out of six model.

The LIQTA ratio has a significant marginal effect for most of the industries and years. However, both significance and magnitude seem to be lower for the hotel and restaurant industry compared to the others. On the other side the magnitude of the marginal effect is strongest for the manufacturing industry. Especially year 2007 is distinguished where LIQTA had a marginal effect of -23.3 for this industry, compared to -2.8 to -11.8 for the other years.

The manufacturing industry is also the industry where R_TA is the best predictor. Here, the ratio is significant in almost all years and does also have a high magnitude of the marginal effect. The ratio is not a good predictor for bankruptcy within the transportation industry though. The estimated marginal effect is positive in three of the years, indicating that a higher return on total assets would have a positive effect on bankruptcy. However, the estimated marginal effect is insignificant over all the six years for this industry so it cannot be concluded that there is a marginal effect.

The last variable is LOGTA, the natural logarithm of the total assets of a firm. This variable has a very significant marginal effect for most of the industries and years. However, no clear industry differences can be recognized when looking over the whole time period.

Table 7.2 in exhibit 7 provides the same test statistics that was provided for the models without industry effects. The first test statistic, the LR-Statistic shows that the overall models are significant with p-values close to zero, similar to the significance of the models without industry effects. The SEE values are very similar to the ones of the models without industry effects and no clear difference can be found. The McFadden R-square values however are higher for all the years, compared to the models without industry effects. This is a reasonable difference since a regression model with more variables should be able to find a better fit than a model with few variables.

4.5 Results from ROC Analysis

When analyzing the results from the ROC analysis the first step is to look at the area under the curve (AUC). As mentioned previously the ROC curve plots sensitivity and 1-specificity and by looking at the AUC one can reduce the ROC-curves performance to a single value as to the expected performance. Another attractive quality about the ROC-curve is that it is insensitive to changes of the distribution in the data sample (Fawcett, 2006). This simplifies the comparison of the ROC curves during the time period in that aspect that the exact ratio of non-bankrupt and bankrupt companies is not the same every year.

Figure 9.1-9.12 in exhibit 9 show ROC curves for the different models on the *estimation sample*. Table 9.1 in the same exhibit shows the AUC values from 2006-2011 with and without industry effects. The table shows that the area under the curve for the different models is between 0.80 and 0.88. All of the areas are significantly different from 0.5 on a 5% level of significance. This means that using the models are better than guessing. According to Han and Kamber, (2006), ROC curves are also a good tool for comparing two classification models. Comparing the two kinds of models, one can see that the average AUC is close to 2.5% higher for the models that contains industry effects on the estimation sample. A larger AUC for the ROC curve with interaction terms would imply that the model with industry effects manages to perform better than the model without the interaction terms. However, table 9.1 in the exhibit also contains the results from a test of equality between the areas of the models. The tests that have been performed are Z-tests testing the equality in AUC between the two models for each year. The null hypothesis is that there is no difference and the alternative hypothesis is that there is a difference. The Z-statistics and corresponding p-values indicate that the null hypothesis of equality cannot be rejected except in one of the years. It can therefore only be concluded that the model with industry effects is better in this year.

When arriving at an appropriate cut-off value the method described in chapter 3 was applied and the value leading to equal sensitivity and specificity was chosen. The cut-off values for all models including and excluding industry effects (IE) are presented in table 4.2 below.

Table 4.2

Cut-Off Values		
Year	*No IE*	*Incl IE*
2006	0,014	0,015
2007	0,024	0,024
2008	0,016	0,015
2009	0,013	0,011
2010	0,018	0,018
2011	0,025	0,019
Avg	0,019	0,017

Cut-off values for the models

Table 9.2 in exhibit 9 presents a summary of a ROC analysis on the *holdout sample*. In this analysis, no cut-off value was looked for since cut-off values had been obtained in the previous analysis. The ROC analysis on the holdout sample solely had the purpose of evaluating the classifying ability between the two kinds of models. In the table, the areas under the curves (AUCs) and their standard errors are presented. Tests of equality between the AUCs were performed in the same way as on the estimation sample, and these results are also presented in the table. The table shows that the AUCs are a little bit higher for the models with industry effects than for the models without industry effects. This is similar to what was found in the estimate on sample. However, none of the differences are statistically significant in this sample and therefore it cannot be concluded that there is any difference in classifying ability between the models.

4.6 Prediction Accuracy

Table 10.1 in exhibit 10 shows the results of prediction accuracy tests on the *estimation sample*. The table presents the sensitivity, specificity, and prediction accuracy for the different models. The results show that the sensitivity, specificity and accuracy all vary between 72% and 80% for the different models and years. Furthermore, the three measures are exactly the same for almost all models. This was expected since the cut-off value was chosen where sensitivity and specificity were equal. Since the accuracy measure is a weighted average of the two measures, all of the three measures will be equal. However, on two of the models the sensitivity and specificity are not exactly the same. The reason for these small differences is that the cut-off values were picked manually and not through an automatic process. Sometimes it was difficult to pick the exact cut-off value that lead to equality between sensitivity and specificity.

In addition to the three measures of classification accuracy, the table also contains the results from a statistical test. The test performed tested the equality in prediction accuracy between the models including and excluding industry effects. The alternative hypothesis was that the prediction accuracy was greater for the models containing industry effects. The results show that the null hypothesis can be rejected in four out of six tests.

Table 10.2 in exhibit 10 shows the results from the tests of prediction accuracy on the *holdout samples*. The table first shows the same measures as the table for the estimation sample. Looking at the table, it is clear that the results differ. Here, sensitivity and specificity are not equal, and this was also expected. The cut-off value was optimized to make sensitivity and specificity equal in the estimation sample but random variation in the samples makes it understandable that this exact equality will not hold when applying the model on another sample.

Comparing the models with and without industry effects, the table shows that the models with industry effects have a little bit higher sensitivity, specificity and prediction accuracy than the ones without industry effects. To test for a difference, tests similar to the ones performed on the estimation sample were done. However, as was discussed previously, the mean of the sensitivity and specificity was here used as the evaluation criterion. The results are presented in the right part of table 10.2 in exhibit 10 and are varying just like the tests on the estimation sample. For three of the years, the model with industry effects performs significantly better than the one without these effects.

5 DISCUSSION

The study has examined the predictive ability of financial ratios across industries and time. The estimated models showed to be in line with the initial hypothesis. The model contained all the kinds of financial variables that were expected. First of all, leverage was assumed to be a good predictor. The relationship showed up to be positive in the models which is a result supported by previous studies. The positive relationship is also in line with the Merton Model that implies that a higher leverage increases the risk that the firm value will fall below the default barrier.

Second, some measure of profitability was expected to be a good predictor. The relationship is negative which is in line with the expectations based on the Merton Model and previous studies. Lastly, after input from employees at Swedbank and its appearance in previous research, liquidity was motivated to be a predictor. This variable turned out to be a good predictor with a high marginal effect on bankruptcy each year. This significant relationship can be interpreted as a sign of market inefficiencies. In a perfect capital market, illiquidity itself should not be a reason for bankruptcy. However, in the real world even a profitable company can go bankrupt if it does not have enough liquidity and access to the capital markets for six months since a creditor can put a company in bankruptcy within this time.

In addition to these three variables, the final model contained a fourth variable – a size measure. Size showed to have a negative relationship with bankruptcy. These results are in line with Ohlson's (1980) study which also showed that size had a negative relationship with bankruptcy. However, other ratios used in previous research did not prove to be as good predictors. For example, Ohlson's variable current assets/current liabilities (or in this study its inverted form) was not good enough to be in the final model of this study. Altman's (1968) capital turnover variable is another example of a variable that did not show to be a good predictor. One reason why these variables were not as good in this study could be because a different population of companies was studied. Another reason is of course the restriction made in this study to use only four variables.

The hypotheses regarding industry differences that were formulated based on Chava & Jarrow's (2004) results are not supported in this study. The results showed to be opposite to the expectations. The first hypothesis was that the manufacturing industry should have a higher leverage coefficient than the transportation industry. In this study however, the transportation industry has a higher coefficient on this ratio. This unexpected difference is also statistically significant in three of the years. The second hypothesis was that the transportation industry should be more sensitive to changes in the return on total assets compared to the manufacturing industry. Also this hypothesis was based on the results from Chava & Jarrow's study and again the results in this study indicate an opposite relationship. However, in this case the opposite relationship is only statistically significant in one of the six years. One reason for these differences could be that the industry classifications are slightly different. In Chava & Jarrow's study, transportation and utility companies are for example pooled together into one category. Another reason could be because the studies are performed in different countries and on data from completely different time periods. The industries have developed over time and probably also their average financial ratios which could be the reason for the models to change.

On average only five interaction terms accounting for industry effects showed to be significant in each year which is less than what was expected initially. This average number is also a little bit lower than the number of significant industry-variables Chava & Jarrow (2004) found, despite using much more variables in the models of this study. One reason why their study found more significant variables could be because their models were adapted to large, public companies. These companies probably have more reliable financial data because of the more strict regulations they are facing. This study on the other hand has examined companies of all different sizes and conditions and there is therefore probably a larger dispersion within the industry categories which makes them less distinct.

The results from the analysis of the classification abilities of the models are varying. The ROC analysis showed that no statistically significant difference could be found between the models with and without industry effects. However, the analysis of the prediction accuracy using specific cut-off values shows that the models incorporating industry differences in three cases perform better than the ones without industry effects. These latter results are in line with Chava & Jarrow's (2004) and Platt & Platt's (1990) studies where they also found that models incorporating industry effects perform better.

More specifically, the prediction accuracy is on average 76.5% for the models without industry effects and 77.7% for the models with industry effects when applied on the holdout sample. These results are not as good as Beaver's (1966), Altman's (1968) or Ohlson's (1980) results of up to 87%, 82%-94% and 85.1% respectively. One possible reason for the different results was discussed above. The argument was that the previous studies are based on large public companies whose financial data may be more reliable and less dispersed. This could make the classification easier. What is particularly interesting in the comparison with the previous studies is that the industry-adapted models in this study that are containing 25 terms did not get as good prediction accuracy as one single financial ratio in Beaver's study. Clearly, one can question the use of advanced prediction models in the light of these results.

6 CONCLUSION

This chapter presents a conclusion of this study and a final discussion on the study's results. The goal is to answer the stated research questions and to fulfill the purpose of the thesis.

6.1 Conclusions

The purpose of this study has been to examine the ability of different financial ratios to predict corporate bankruptcy across industries and time. The study found four financial variables that were able to predict bankruptcy and which the analysis was concentrated to.

First, logistic regression models both excluding and including industry effects were estimated for each year between 2006 and 2011. The models were then analyzed for differences between the years and industries. Leverage and size showed a decreasing trend over the years, and statistical tests showed that there was a statistically significant difference between their coefficients for 2006 and 2011. From this analysis, it can be concluded that the variation in marginal effect on bankruptcy over time for the two variables leverage and size is statistically significant. However, also the coefficients for the other variables varied a lot, and tests between other combinations of years may therefore show other results.

The implications of the results are that bankruptcy prediction models vary depending on the time of the estimation. Therefore it can be concluded that bankruptcy prediction models preferably should be used on company data from the same time period as it was estimated. However, as was discussed earlier, a bankruptcy prediction model can only be estimated in retrospect. This leads to that one can question the use of these kinds of models. One can especially question the common practice of pooling data from many years in a static model since two of the variables showed to have a trend which makes older data less relevant than more recent one.

Differences were not only found across time but also across industries. The analysis showed that different financial ratios where significant for different industries. For example, for some of the industries, the return on total assets ratio did not have any significant marginal effect on bankruptcy. Some of the other differences across industries that were found were for example that leverage has a higher marginal effect on bankruptcy for the transportation industry compared to the manufacturing industry and that the liquidity ratio has a lower marginal effect on bankruptcy for the hotel and restaurant industry. However not many of the industry differences were significant.

The estimated models were also tested. The tests showed that the performance of the models was relatively low compared to previous studies. The tests also showed that including the industry effects in the model increased the classifying ability, sensitivity and specificity only a little bit in the tested samples. When different tests of equality between the models were performed, the results were ambiguous. The tests of equality in the area under the ROC showed that no differences were statistically significant on the holdout sample. However, when a test of equality between the mean of the sensitivity and specificity for the two models was performed, the difference was significant in three out of six years. In these three years the accuracy was increased by incorporating the industry differences.

The ambiguity between the two tests makes it harder to draw any conclusions. Yet, by looking at the definitions of the measures, some differences can be found. While the area under the ROC curve is a measure of the classifying ability of a model *regardless* any specific cut-off value, the mean of the sensitivity and specificity is a measure of classification accuracy using a *specific* cut-off value. Therefore it cannot be concluded that there exist any difference in classifying ability for the two models regardless cut-off value but that it *does* exist a difference when using these specific cut-off values in three of the six years.

6.2 Suggestions for Further Research

This study set out to answer questions regarding industry effects on bankruptcy prediction. Although the stated questions have been answered, new ones have surfaced along the way.

In the interaction with Swedbank it became obvious that much more than accounting data is considered when evaluating a company. Future research could therefore try a new perspective on a broader range of variables and not only financial variables to make the bankruptcy prediction models more successful. Such variables can be for example the private economy of the CEO or the change of board members.

The results in this study show that the bankruptcy prediction models vary over time. However, there are still questions about how the variation is connected to macroeconomic factors. An interesting angle would therefore be to analyze the macroeconomic effects on the model and see if an incorporation of these effects in the model can increase the performance.

In this study only five industries have been studied. Future research on the subject could therefore analyze other industries and choose another methodology in this industry selection. It would for example be interesting to choose the most dissimilar industries in some way in an attempt to make the industry-adaptation in the model more relevant.

One question that has surfaced during this study is what effects different corporate rules and regulations have on the predictive ability of financial ratios. Does the performance of a prediction model vary across countries because of such differences? One idea would be to exchange the industry dummies in this study for country dummies if these differences would appear to be large.

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Exhibit 1 – List of Financial Ratios

Table 1.1

List and Explanation of Collected Financial Ratios		
Code	***Name***	***Definition***
	Return Structure	
R_E	Return on equity	Net income/adjusted equity
R_TA	Return on total capital	Operating profit + fin incomes as % of total assets
INTD	Interest on debt	Fin. expenses/sum of appropriation & debt including suspended tax debt
RMG	Risk margin on total capital	Difference in % between return on total capital and interest on debt
R_OPC	Return on operating capital	Operating profit + fin income as % of operating capital
OPRMG	Operating Risk margin	Difference (%) in return on operating capital and interst rate
	Profit Structure	
OPMG	Operating margin	Operating profit as % of net turn-over
PRMG	Profit margin	Net income as % of net turn-over
INTCOV	Interest coverage	Operating profit including fin revenues/ fin. costs
OPPREMPL	Operating profit per employee	Operating profit after ammortization/ average number of employees
	Income/Cost Structure	
SAEMPL	Net sales per employee	Net turnover/avg number of employees
CEMPL	Cost per employee tkr	Employee costs/avg number of employees

Table 1.1, continued

List and Explanation of Collected Financial Ratios (Cont'd)		
Code	***Name***	***Definition***
	Capital Structure	
SOLID	Solidity	Adjusted equity as % of total assets
LEV	Leverage	Total liabilities/total assets
CAPTO	Capital turnover ratio	Net turnover/total assets
WCAPSA	Working capital in relation to turnover	Working capital as % of net turnover
WCAPTA	Working capital in relation to total assets	Working capital as % of total assets
STDSA	Short-term debt in relation to turnover	Short-term debt as % of net turnover
RECSA	Receivables in relation to turnover	Receivables as % of net turnover
LIQSTD	Cash liquidity	Current assets excluding inventory etc, as % of short-term debt
LIQSA	Liquidity in relation to turnover	Liquidity/turnover
LIQTA	Liquidity in relation to total assets	Liquidity/total assets
INVSA	Inventory and ongoing activity etc over sales	Inventory and ongoing activity etc as % of net turnover
INVTO	Inventory turnover rate	Cost of goods sold/average inventory
	Development	
CHSA	Change in sales	Difference between t and t-1 net turnover, as a % of t-1 net turnover
	Firm Size	
LOGTA	Log total assets	Ln(total assets)

Exhibit 2 – Bankruptcies across Industries

Table 2.1

Count % Row	Number of Bankruptcies per Year						Total number of observations		
INDUSTRY SECTOR	2006	2007	2008	2009	2010	2011	NON-BANKRUPT	BANKRUPT	TOTAL
Uncategorized	239	301	545	524	113	1	2557	1723	4280
	44,51%	47,63%	58,98%	54,47%	18,05%	0,17%	59,74%	40,26%	100%
Sewer, Waste, Electricity and Water	0	1	2	1	0	1	3000	5	3005
	0%	0,22%	0,42%	0,20%	0%	0,17%	99,83%	0,17%	100%
Staffing and Employment Agencies	2	13	13	1	15	16	2543	60	2603
	0,75%	3,89%	3,35%	0,23%	2,82%	2,47%	97,69%	2,31%	100%
Industry and Employer Organizations	0	0	0	0	0	0	392	0	392
	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	100,00%
Building, Design, & Decoration Businesses	72	155	113	89	151	190	48386	770	49156
	1,14%	2,22%	1,46%	1,08%	1,64%	1,78%	98,43%	1,57%	100,00%
Data, IT & Telecom	12	23	8	6	18	11	11094	78	11172
	0,91%	1,51%	0,46%	0,31%	0,83%	0,44%	99,30%	0,70%	100,00%
Retail	37	74	54	41	82	98	29827	386	30213
	0,92%	1,68%	1,14%	0,80%	1,45%	1,57%	98,72%	1,28%	100,00%
Real Estate	40	72	60	56	50	16	14939	294	15233
	2,03%	3,27%	2,49%	2,15%	1,75%	0,50%	98,07%	1,93%	100,00%
Business Services	9	27	8	4	23	19	6065	90	6155
	1,16%	3,10%	0,84%	0,38%	1,97%	1,43%	98,54%	1,46%	100,00%
Health Care	5	14	5	10	12	11	9097	57	9154
	0,47%	1,17%	0,37%	0,63%	0,66%	0,51%	99,38%	0,62%	100,00%
Hair & Beauty	3	2	1	0	1	3	1239	10	1249
	2,27%	1,20%	0,52%	0,00%	0,40%	1,01%	99,20%	0,80%	100,00%
Hotels & Restaurants	45	82	52	43	57	44	18569	323	18892
	2,05%	3,23%	1,83%	1,34%	1,52%	1,01%	98,29%	1,71%	100,00%
Agriculture, Forestry, Hunting & Fishing	2	13	5	5	6	9	6181	40	6221
	0,25%	1,45%	0,51%	0,47%	0,52%	0,68%	99,36%	0,64%	100,00%
Legal, Business and Consulting Services	7	13	13	1	13	4	10060	51	10111
	0,60%	0,97%	0,84%	0,06%	0,66%	0,17%	99,50%	0,50%	100,00%
Culture & Entertainment	6	4	1	0	8	2	3511	21	3532
	1,31%	0,79%	0,18%	0,00%	1,22%	0,26%	99,41%	0,59%	100,00%
Food Production	8	10	3	1	14	13	4809	49	4858
	1,15%	1,37%	0,39%	0,12%	1,59%	1,36%	98,99%	1,01%	100,00%
Media	1	4	0	1	6	5	2933	17	2950
	0,26%	0,91%	0,00%	0,20%	1,09%	0,83%	99,42%	0,58%	100,00%
Motor Vehicle Dealing	2	5	0	1	6	5	4036	19	4055
	0,33%	0,79%	0,00%	0,15%	0,83%	0,65%	99,53%	0,47%	100,00%
Public Administration	0	0	0	0	0	0	96	0	96
	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	100,00%	0,00%	100,00%
Other Consumer Services	2	0	1	1	4	3	1485	11	1496
	1,17%	0,00%	0,46%	0,39%	0,33%	0,81%	99,26%	0,74%	100,00%
Wholesale	16	53	23	4	59	53	35103	208	35311
	0,32%	0,98%	0,40%	0,07%	0,93%	0,78%	99,41%	0,59%	100,00%
Advertisement and PR	7	17	10	6	19	24	4739	83	4822
	1,17%	2,50%	1,31%	0,75%	2,10%	2,23%	98,28%	1,72%	100,00%
Reparation & Installation	6	13	11	5	11	24	8448	70	8518
	0,53%	1,04%	0,82%	0,35%	0,70%	1,35%	99,18%	0,82%	100,00%
Travel Agencies & Tourism	2	5	1	1	1	3	1363	13	1376
	1,08%	2,45%	0,46%	0,43%	0,39%	1,07%	99,06%	0,94%	100,00%
Technical Consulting	4	8	4	1	13	13	6048	43	6091
	0,53%	0,95%	0,42%	0,10%	1,11%	1,16%	99,29%	0,71%	100,00%
Manufacturing	34	96	55	38	87	109	45166	419	45585
	0,50%	1,34%	0,73%	0,50%	1,09%	1,28%	99,08%	0,92%	100,00%
Transportation & Storage	31	68	69	46	73	68	21485	355	21840
	1,04%	2,08%	1,97%	1,25%	1,82%	1,54%	98,37%	1,63%	100,00%
Education, Research and Development	6	9	5	0	9	17	6649	46	6695
	0,74%	1,00%	0,49%	0,00%	0,69%	1,14%	99,31%	0,69%	100,00%
Leasing	2	4	2	1	3	4	2110	16	2126
	0,71%	1,32%	0,60%	0,29%	0,75%	0,86%	99,25%	0,75%	100,00%
Total	600	1086	1064	887	854	766	311930	5257	317187
	1,43%	2,35%	2,11%	1,64%	1,45%	1,16%	98,34%	1,66%	100,00%

Exhibit 3 – Univariate Analysis

Table 3.1

Results from Univariate Analysis						
	Bankrupt Firms		Non-bankrupt Firms		Test for Equality of Means	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**T-statistic**	**Prob.**
CAPTO	3.836845	4.517157	2.770288	2.228241	-15.72162	0.0000
CEMPL	358.2010	121.2354	414.2719	134.7106	13.98054	0.0000
CHSA	254.2236	5861.756	120.3419	11103.12	-0.406508	0.6844
INVSA	7.944917	14.03755	8.184782	21.63113	0.373464	0.7088
INVTO	4.676345	55.40156	10.39976	176.8127	1.092656	0.2745
LEV	1.080848	0.722997	0.664630	0.460936	-29.98860	0.0000
LIQSA	2.718817	11.35666	10.21879	46.59154	5.435154	0.0000
LIQSTD	80.59738	173.6995	135.2942	135.6379	13.46744	0.0000
LIQTA	0.078033	0.131240	0.183870	0.193750	18.39261	0.0000
LOGTA	8.120192	1.185970	9.009671	1.414194	21.14153	0.0000
OPMG	-6.100736	20.79664	2.901071	118.3873	2.567857	0.0102
OPPREMPL	-49.13155	174.6787	84.07490	230.0721	19.47841	0.0000
PRMG	-5.689895	20.53129	3.353799	118.0031	2.588217	0.0096
R_E	-143.5224	1177.598	16.77627	868.6558	6.154575	0.0000
R_OPC	-10.46414	1129.321	27.66481	2640.780	0.487087	0.6262
R_TA	-17.32813	65.85460	9.918002	24.24930	36.13088	0.0000
RECSA	8.886161	10.15290	9.832895	19.91617	1.602774	0.1090
SAEMPL	1248.840	1189.504	1738.360	2044.841	8.067216	0.0000
SOLID	-8.273392	73.73490	33.55036	39.72009	34.73817	0.0000
STDSA	30.51974	29.44296	23.29120	70.22046	-3.472902	0.0005
WCAPSA	-4.511788	28.06559	9.182347	75.06895	6.155869	0.0000
WCAPTA	-0.160505	0.708506	0.172803	0.401295	27.46208	0.0000

The table shows the mean and standard deviation on 22 different financial variables for bankrupt and non-bankrupt companies in the estimation sample. The table also shows the results from tests of equality between the two groups. The null hypothesis is that there is no difference between the means for bankrupt and non-bankrupt companies. The alternative hypothesis is that there is a difference.

Exhibit 4 – Financial Ratios across Industries

Table 4.1

	CAPTO		CEMPL		LEV		LIQSA		LIQSTD		LIQTA		LOGTA		OPMG		OPPREMPL	
	NB	B	NB	B	NB	B	NB	B	NB	B	NB	B	NB	B	NB	B	NB	B
Building	2.71	3.98	444	382	0.66	1.04	11.2	2.4	153.9	89.7	0.22	0.08	8.72	8.02	0.05	-0.02	90.3	-13.5
Hotel & Restaurant	3.55	4.93	317	259	0.80	1.39	9.7	4.0	112.8	62.5	0.25	0.14	8.12	7.27	0.02	-0.11	34.4	-46.5
Manufacturing	1.90	2.33	443	394	0.61	1.03	10.9	2.9	146.3	72.0	0.13	0.03	9.72	8.85	0.01	-0.23	113.9	-76.0
Retail	4.22	4.76	374	343	0.66	1.07	7.6	3.4	103.7	53.4	0.21	0.08	8.82	8.18	0.01	-0.11	71.2	-96.2
Transport	2.12	2.78	429	383	0.71	1.10	11.5	1.9	130.4	92.0	0.15	0.05	9.25	8.39	0.04	-0.02	81.6	-33.7
All	2.78	3.75	414	360	0.67	1.10	10.3	2.9	134.9	76.7	0.19	0.08	9.01	8.15	0.03	-0.09	85.9	-47.2

Table 4.1, continued

	PRMG		R_E		R_TA		SAEMPL		SOLID		STDSA		WCAPSA		WCAPTA	
	NB	B	NB	B	NB	B	NB	B	NB	B	NB	B	NB	B	NB	B
Building	0.06	-0.02	0.32	-0.40	0.13	-0.10	1398	1160	34.3	-4.2	22.7	28.4	11.2	-1.4	0.23	-0.09
Hotel & Restaurant	0.03	-0.11	0.04	-0.87	0.06	-0.37	883	821	20.0	-38.8	22.5	31.6	-2.8	-13.3	-0.06	-0.50
Manufacturing	0.02	-0.22	0.11	-0.92	0.09	-0.19	1748	920	38.8	-2.9	27.7	57.8	14.0	-17.5	0.22	-0.09
Retail	0.02	-0.10	0.19	-3.27	0.10	-0.18	2487	4464	34.3	-6.7	17.5	32.8	9.7	-3.5	0.22	-0.04
Transport	0.05	-0.02	0.07	-0.11	0.07	-0.08	1921	903	29.5	-10.2	26.4	27.9	1.4	-10.7	0.01	-0.24
All	0.03	-0.08	0.18	-1.01	0.10	-0.17	1722	1575	33.3	-10.3	23.6	35.0	8.8	-7.9	0.17	-0.16

The table contains the 17 financial variables that passed the previous univariate test. The table shows the mean of the financial variables for bankrupt and non-bankrupt companies in the estimation sample, belonging to the five selected industries. The table also split up the five industries and shows the means for each industry respectively.

Note: NB=Mean of non-bankrupt firms

B=Mean of bankrupt firms

Exhibit 5 – Correlations among Financial Ratios

Table 5.1

	CAPTO	CEMPL	LEV	LIQSA	LIQSTD	LIQTA	LOGTA	OPMG	OPPREMPL	PRMG	R_E	R_TA	SAEMPL	SOLID	STDSA	WCAPSA	WCAPTA
CAPTO	1.00	-0.11	0.24	-0.08	-0.11	0.09	-0.37	0.00	-0.05	0.00	0.03	-0.06	0.15	-0.26	-0.10	-0.04	-0.16
CEMPL		1.00	-0.09	0.05	0.05	0.00	0.40	-0.02	0.12	-0.02	-0.00	0.05	0.34	0.09	0.05	0.00	0.05
LEV			1.00	-0.08	-0.21	-0.24	-0.13	-0.02	-0.08	-0.02	-0.01	-0.40	-0.02	**-0.99**	0.05	-0.11	**-0.78**
LIQSA				1.00	0.14	0.21	0.02	**-0.50**	-0.01	-0.48	-0.01	0.00	-0.02	0.09	0.32	**0.52**	0.09
LIQSTD					1.00	0.28	0.04	0.01	0.05	0.01	0.01	0.07	-0.00	0.23	-0.03	0.13	0.25
LIQTA						1.00	-0.19	0.01	0.06	0.01	0.03	0.22	-0.02	0.26	-0.04	0.12	0.35
LOGTA							1.00	0.01	0.13	0.01	-0.00	0.05	0.32	0.14	0.08	-0.00	0.00
OPMG								1.00	0.07	1.00	0.06	0.13	0.01	0.02	-0.39	-0.11	0.03
OPPREMPL									1.00	0.07	0.06	0.20	0.31	0.08	-0.04	0.03	0.07
PRMG										1.00	0.06	0.13	0.01	0.02	-0.38	-0.10	0.03
R_E											1.00	0.14	0.01	0.01	-0.05	0.03	0.02
R_TA												1.00	0.05	0.41	-0.07	0.04	0.38
SAEMPL													1.00	0.02	-0.02	-0.00	0.02
SOLID														1.00	-0.06	0.12	**0.77**
STDSA															1.00	**-0.57**	-0.10
WCAPSA																1.00	0.20
WCAPTA																	1.00

The table shows the correlations among the remaining financial variables, based on companies from the five selected industries in the estimation sample.

Exhibit 6 – Prediction Models excluding Industry Effects

Table 6.1 – Prediction Models

Annual Bankruptcy Prediction Models without Industry-Effects

Variable		2006	2007	2008	2009	2010	2011
Intercept	Coefficient	1.5842	0.5149	1.2538	0.3777	0.0758	-0.1284
	Std. Error	0.9204	0.6509	0.6800	0.7456	0.5579	0.4499
	Z-Statistic	1.7213	0.7911	1.8437	0.5066	0.1359	-0.2855
	P-value	0.0852	0.4289	0.0652	0.6125	0.8919	0.7753
LEV	Coefficient	0.9344	1.3289	0.5758	0.5138	0.3568	0.1776
	Std. Error	0.2859	0.2179	0.1559	0.1681	0.1230	0.0422
	Z-Statistic	3.2686	6.0997	3.6936	3.0568	2.9021	-4.2059
	P-value	0.0011	0.0000	0.0002	0.0022	0.0037	0.0000
LIQTA	Coefficient	-4.2609	-4.9960	-3.1251	-5.1100	-6.0922	-5.8321
	Std. Error	0.8608	0.6841	0.5996	0.8044	0.7144	0.6202
	Z-Statistic	-4.9498	-7.3032	-5.2121	-6.3527	-8.5281	-9.4038
	P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R_TA	Coefficient	-0.6271	-1.5396	-1.3422	-0.7721	-1.3474	-0.9212
	Std. Error	0.4146	0.2912	0.2172	0.2269	0.2028	0.1699
	Z-Statistic	-1.5127	-5.2879	-6.1805	-3.4028	-6.6433	-5.4227
	P-value	0.1304	0.0000	0.0000	0.0007	0.0000	0.0000
LOGTA	Coefficient	-0.7447	-0.5647	-0.6439	-0.5570	-0.4491	-0.3733
	Std. Error	0.1008	0.0677	0.0749	0.0821	0.0614	0.0521
	Z-Statistic	-7.3867	-8.3418	-8.5999	-6.7842	-7.3166	-7.1632
	P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

The table shows the bankruptcy prediction models for each year that was estimated without industry effects.

Table 6.2 – Test Statistics for the Models

	2006	2007	2008	2009	2010	2011
LR Statistic	184.7916	412.0594	294.4631	205.6030	304.8784	240.0070
Prob(LR-Stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SEE	0.1002	0.1312	0.1156	0.0984	0.1189	0.1206
McFadden R-Squared	0.1454	0.1828	0.1537	0.1310	0.1311	0.0907

The table shows the test statistics for the estimated prediction models without industry effects.

Table 6.3

Test of Coefficient Equality between Years					
Variable		**2006**	**2011**	**Z-Statistic**	**P-value**
Intercept	Coefficient	1.5842	-0.1284	1.6718	0.0946
	Std. Error	0.9204	0.4499		
LEV	Coefficient	0.9344	0.1776	2.6187	0.0088
	Std. Error	0.2859	0.0422		
LIQTA	Coefficient	-4.2609	-5.8321	1.4809	0.1386
	Std. Error	0.8608	0.6202		
R_TA	Coefficient	-0.6271	-0.9212	0.6564	0.5116
	Std. Error	0.4146	0.1699		
LOGTA	Coefficient	-0.7447	-0.3733	-3.2727	0.0011
	Std. Error	0.1008	0.0521		

The table shows equality tests on the different coefficients of the different variables in the prediction models without industry effects. The tests test the equality in the coefficients between 2006 and 2011.

Note:

Null-hypothesis: Coefficient for 2006=Coefficient for 2011

Alternative hypothesis: Coefficient for 2006≠Coefficient for 2011

Exhibit 7 – Prediction Models including Industry Effects

Table 7.1

Bankruptcy Prediction Models with Industry-Effects

Variable		2006	2007	2008	2009	2010	2011
Intercept	Coefficient	4.2393	1.2297	-0.5933	-6.6985	-4.5119	-2.4208
	Std. Error	2.9099	1.6048	1.9888	1.8219	1.2113	1.0728
	Z Statistic	1.4568	0.7663	-0.2983	-3.6767	-3.7249	-2.2566
	P-value	0.1452	0.4435	0.7654	**0.0002**	**0.0002**	**0.0240**
LEV	Coefficient	1.2669	2.0295	2.2513	2.5687	1.4804	1.3687
	Std. Error	0.7665	0.6744	0.7711	0.5524	0.4206	0.3667
	Z Statistic	1.6530	3.0093	2.9198	4.6503	3.5200	3.7325
	P-value	0.0983	**0.0026**	**0.0035**	**0.0000**	**0.0004**	**0.0002**
LIQTA	Coefficient	-11.8160	-23.3286	-4.4578	-2.7891	-9.5732	-7.7609
	Std. Error	4.3583	6.7504	2.6458	2.6762	3.2042	2.2765
	Z Statistic	-2.7112	-3.4559	-1.6849	-1.0422	-2.9877	-3.4091
	P-value	0.0670	**0.0005**	0.0920	0.2973	**0.0028**	**0.0007**
R_TA	Coefficient	-2.7976	-2.6551	-0.9946	-1.1919	-1.7868	-1.0302
	Std. Error	0.8839	0.7162	0.5398	0.6094	0.4718	0.3899
	Z Statistic	-3.1652	-3.7074	-1.8424	-1.9558	-3.7872	-2.6424
	P-value	**0.0016**	**0.0002**	0.0654	0.0505	**0.0002**	**0.0082**
LOGTA	Coefficient	-1.1188	-0.6733	-0.6129	-0.0334	-0.0705	-0.2471
	Std. Error	0.3216	0.1562	0.1954	0.1642	0.1138	0.1018
	Z Statistic	-3.4788	-4.3100	-3.1368	-0.2034	-0.6195	-2.4282
	P-value	**0.0005**	**0.0000**	**0.0017**	0.8389	0.5356	**0.0152**
LEV* BUILDING	Coefficient	-1.2373	0.4080	-1.5521	-0.5326	-0.1832	-0.1087
	Std. Error	0.8567	0.8545	0.8150	0.7490	0.5794	0.4796
	Z Statistic	-1.4442	0.4775	-1.9044	-0.7111	-0.3163	-0.2265
	P-value	0.1487	0.6330	0.0569	0.4771	0.7518	0.8208
LEV* RETAIL	Coefficient	1.4178	0.3434	-1.1605	-1.5024	-1.4038	-1.2464
	Std. Error	1.5294	0.9432	0.9591	0.8663	0.4446	0.3757
	Z Statistic	0.9270	0.3641	-1.2100	-1.7343	-3.1577	-3.3175
	P-value	0.3539	0.7158	0.2263	0.0829	**0.0016**	**0.0009**

Table 7.1, continued

Bankruptcy Prediction Models with Industry-Effects (cont'd)

Variable		2006	2007	2008	2009	2010	2011
LEV*HR	Coefficient	-0.3875	-1.3700	-2.3245	-2.5990	-1.3773	-1.6068
	Std. Error	0.8701	0.7367	0.8262	0.6261	0.4892	0.3754
	Z Statistic	-0.4453	-1.8598	-2.8135	-4.1510	-2.8152	-4.2805
	P-value	0.6561	0.0629	**0.0049**	**0.0000**	**0.0049**	**0.0000**
LEV* TRANSPORT	Coefficient	6.3292	2.1787	3.1382	3.6150	1.3636	1.0831
	Std. Error	1.7188	1.4776	1.4419	1.5451	0.9045	0.7703
	Z Statistic	3.6823	1.4745	2.1764	2.3397	1.5076	1.4061
	P-value	**0.0002**	0.1403	**0.0295**	**0.0193**	0.1317	0.1597
LIQTA* BUILDING	Coefficient	7.6640	21.0810	1.4815	-1.0246	4.0801	2.1982
	Std. Error	4.5876	6.8173	2.8010	2.9631	3.4008	2.5343
	Z Statistic	1.6706	3.0923	0.5289	-0.3458	1.1998	0.8674
	P-value	0.0948	**0.0020**	0.5969	0.7295	0.2302	0.3857
LIQTA* RETAIL	Coefficient	4.2720	20.0313	3.1255	-5.7704	3.1768	3.7414
	Std. Error	5.0663	6.9376	3.0547	3.8690	3.6351	2.5670
	Z Statistic	0.8432	2.8874	1.0232	-1.4914	0.8739	1.4575
	P-value	0.3991	**0.0039**	0.3062	0.1358	0.3822	0.1450
LIQTA*HR	Coefficient	10.7025	18.8219	3.3167	0.4120	0.8256	4.8891
	Std. Error	4.5401	6.9150	2.8831	3.0174	3.7557	2.6794
	Z Statistic	2.3573	2.7219	1.1504	0.1365	0.2198	1.8247
	P-value	**0.0184**	**0.0065**	0.2500	0.8914	0.8260	0.0680
LIQTA* TRANSPORT	Coefficient	3.0797	17.4399	1.0485	-5.1051	6.7454	4.1584
	Std. Error	6.0381	7.1342	3.4947	4.4918	3.6090	2.9997
	Z Statistic	0.5101	2.4446	0.3000	-1.1365	1.8691	1.3863
	P-value	0.6100	**0.0145**	0.7641	0.2557	0.0616	0.1657

Table 7.1, continued

Bankruptcy Prediction Models with Industry-Effects (cont'd)

Variable		2006	2007	2008	2009	2010	2011
R_TA* BUILDING	Coefficient	0.6844	2.0514	-0.1375	0.4450	1.2457	-0.0377
	Std. Error	1.2747	1.0395	0.6730	0.8603	0.6731	0.5230
	Z Statistic	0.5369	1.9734	-0.2043	0.5173	1.8508	-0.0720
	P-value	0.5913	**0.0484**	0.8382	0.6049	0.0642	0.9426
R_TA* RETAIL	Coefficient	4.1436	-1.1457	-2.5073	2.7591	0.0462	0.8168
	Std. Error	1.6723	1.1225	0.8712	1.3061	0.6655	0.4039
	Z Statistic	2.4778	-1.0206	-2.8781	2.1124	0.0694	2.0224
	P-value	**0.0132**	0.3074	**0.0040**	**0.0346**	0.9447	**0.0431**
R_TA*HR	Coefficient	2.7560	1.3659	-0.3400	-0.2926	1.0598	-0.0596
	Std. Error	1.0152	0.8770	0.7074	0.7475	0.6462	0.5173
	Z Statistic	2.7148	1.5575	-0.4807	-0.3915	1.6399	-0.1152
	P-value	**0.0066**	0.1194	0.6308	0.6955	0.1010	0.9083
R_TA* TRANS PORT	Coefficient	1.3002	2.6283	-0.1829	1.6439	2.6881	1.2153
	Std. Error	1.8980	1.4829	0.7358	1.4578	1.1433	0.7506
	Z Statistic	0.6851	1.7724	-0.2486	1.1277	2.3511	1.6191
	P-value	0.4933	0.0763	0.8037	0.2595	**0.0187**	0.1054
LOGTA* BUILDING	Coefficient	0.6556	0.2154	-0.1060	-0.6502	-0.4058	0.0047
	Std. Error	0.3670	0.1999	0.2425	0.2325	0.1683	0.1402
	Z Statistic	1.7862	1.0778	-0.4374	-2.7961	-2.4119	0.0337
	P-value	0.0741	0.2811	0.6618	**0.0052**	**0.0159**	0.9731
LOGTA* RETAIL	Coefficient	0.5219	0.1147	0.0845	-0.4226	-0.7947	0.0913
	Std. Error	0.4147	0.2522	0.2912	0.2923	0.2413	0.1633
	Z Statistic	1.2584	0.4550	0.2901	-1.4456	-3.2938	0.5591
	P-value	0.2082	0.6491	0.7717	0.1483	**0.0010**	0.5761

Table 7.1, continued

Bankruptcy Prediction Models with Industry-Effects (cont'd)

Variable		2006	2007	2008	2009	2010	2011
LOGTA*HR	Coefficient	0.4480	0.1437	-0.1287	-0.2061	-0.4201	-0.2856
	Std. Error	0.3993	0.2449	0.3088	0.2602	0.1910	0.2502
	Z Statistic	1.1220	0.5867	-0.4168	-0.7922	-2.1999	-1.1416
	P-value	0.2619	0.5574	0.6768	0.4283	**0.0278**	0.2536
LOGTA* TRANS PORT	Coefficient	0.0955	-0.1498	0.0504	-0.6366	-0.2961	-0.0765
	Std. Error	0.4443	0.2491	0.2613	0.2822	0.1980	0.1959
	Z Statistic	0.2148	-0.6013	0.1929	-2.2558	-1.4959	-0.3906
	P-value	0.8299	0.5476	0.8471	**0.0241**	0.1347	0.6961
BUILDING	Coefficient	-4.0555	-2.6401	2.5540	6.9026	4.1042	0.1758
	Std. Error	3.2831	1.9849	2.3516	2.3580	1.6770	1.4241
	Z Statistic	-1.2353	-1.3300	1.0861	2.9273	2.4473	0.1234
	P-value	0.2167	0.1835	0.2774	**0.0034**	**0.0144**	0.9018
RETAIL	Coefficient	-5.1290	-1.8713	-0.0821	5.7584	8.0601	0.0917
	Std. Error	3.8841	2.4684	2.8200	2.9063	2.1716	1.5744
	Z Statistic	-1.3205	-0.7581	-0.0291	1.9813	3.7116	0.0582
	P-value	0.1867	0.4484	0.9768	**0.0476**	**0.0002**	0.9536
HR	Coefficient	-3.5295	-0.6426	2.4731	4.6868	5.5485	2.4512
	Std. Error	3.5047	2.2554	2.7538	2.5179	1.7717	2.0463
	Z Statistic	-1.0071	-0.2849	0.8981	1.8614	3.1317	1.1979
	P-value	0.3139	0.7757	0.3691	0.0627	**0.0017**	0.2310
TRANS PORT	Coefficient	-5.5270	-0.7405	-2.4053	3.6764	1.7772	-0.6474
	Std. Error	4.1760	2.5623	2.8887	3.1134	2.1941	2.0696
	Z Statistic	-1.3235	-0.2890	-0.8327	1.1808	0.8100	-0.3128
	P-value	0.1857	0.7726	0.4050	0.2377	0.4180	0.7544

The table shows the estimated bankruptcy prediction models for each year with industry effects included.

Table 7.2 – Test Statistics for the Models

	2006	2007	2008	2009	2010	2011
LR Statistic	251.0263	490.7448	392.0353	309.5832	367.2819	359.1553
Prob(LR-Stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SEE	0.0985	0.1302	0.1133	0.0967	0.1177	0.1200
McFadden R-Squared	0.1975	0.2177	0.2046	0.1972	0.1579	0.1357

The table shows the test statistics for the estimated prediction models including industry effects.

Exhibit 8 – Total Marginal Effects for Each Industry

Table 8.1 – Manufacturing Industry

Total Marginal Effects, Manufacturing Industry						
Variable	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Intercept						
Coefficient	4.2393	1.2297	-0.5933	-6.6985	-4.5119	-2.4208
Std Error	2.9099	1.6048	1.9888	1.8219	1.2113	1.0728
Z-Statistic	1.4568	0.7663	-0.2983	-3.6767	-3.7249	-2.2566
P-Value	0.1452	0.4435	0.7654	0.0002	0.0002	0.0240
LEV						
Coefficient	1.2669	2.0295	2.2513	2.5687	1.4804	1.3687
Std Error	0.7665	0.6744	0.7711	0.5524	0.4206	0.3667
Z-statistic	1.6530	3.0093	2.9198	4.6503	3.5200	3.7325
P-Value	0.0983	0.0026	0.0035	0.0000	0.0004	0.0002
LIQTA						
Coefficient	-11.8160	-23.3286	-4.4578	-2.7891	-9.5732	-7.7609
Std Error	4.3583	6.7504	2.6458	2.6762	3.2042	2.2765
Z-statistic	-2.7112	-3.4559	-1.6849	-1.0422	-2.9877	-3.4091
P-Value	0.0670	0.0005	0.0920	0.2973	0.0028	0.0007
R_TA						
Coefficient	-2.7976	-2.6551	-0.9946	-1.1919	-1.7868	-1.0302
Std Error	0.8839	0.7162	0.5398	0.6094	0.4718	0.3899
Z-statistic	-3.1652	-3.7074	-1.8424	-1.9558	-3.7872	-2.6424
P-Value	0.0016	0.0002	0.0654	0.0505	0.0002	0.0082
LOGTA						
Coefficient	-1.1188	-0.6733	-0.6129	-0.0334	-0.0705	-0.2471
Std Error	0.3216	0.1562	0.1954	0.1642	0.1138	0.1018
Z-statistic	-3.4788	-4.3100	-3.1368	-0.2034	-0.6195	-2.4282
P-Value	0.0005	0.0000	0.0017	0.8389	0.5356	0.0152

Table 8.2 – Building Industry

Total Marginal Effects, Building Industry						
Variable	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Intercept						
Coefficient	0.1838	-1.4103	1.9607	0.2040	-0.4078	-2.2451
Std Error	1.5202	1.1682	1.2549	1.4970	1.1598	0.9366
Z-Statistic	0.1209	-1.2073	1.5624	0.1363	-0.3516	-2.3971
P-Value	0.9038	0.2273	0.1182	0.8916	0.7252	0.0165
LEV						
Coefficient	0.0297	2.4375	0.6992	2.0362	1.2971	1.2601
Std Error	0.3828	0.5247	0.2640	0.5058	0.3985	0.3092
Z-statistic	0.0775	4.6458	2.6483	4.0257	3.2550	4.0758
P-Value	0.9382	0.0000	0.0081	0.0001	0.0011	0.0000
LIQTA						
Coefficient	-4.1520	-2.2476	-2.9763	-3.8137	-5.4931	-5.5627
Std Error	1.4323	0.9526	0.9195	1.2720	1.1396	1.1136
Z-statistic	-2.8989	-2.3594	-3.2369	-2.9982	-4.8204	-4.9950
P-Value	0.0037	0.0183	0.0012	0.0027	0.0000	0.0000
R_TA						
Coefficient	-2.1132	-0.6037	-1.1321	-0.7469	-0.5411	-1.0679
Std Error	1.5511	1.2623	0.8627	1.0542	0.8220	0.6523
Z-statistic	-1.3624	-0.4783	-1.3123	-0.7085	-0.6583	-1.6371
P-Value	0.1731	0.6325	0.1894	0.4786	0.5103	0.1016
LOGTA						
Coefficient	-0.4632	-0.4579	-0.7190	-0.6836	-0.4763	-0.2424
Std Error	0.1768	0.1247	0.1436	0.1647	0.1240	0.0965
Z-statistic	-2.6201	-3.6725	-5.0082	-4.1512	-3.8418	-2.5115
P-Value	0.0088	0.0002	0.0000	0.0000	0.0001	0.0120

Table 8.3 – Retail Industry

Total Marginal Effects, Retail Industry						
Variable	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Intercept						
Coefficient	-0.8897	-0.6416	-0.6755	-0.9401	3.5482	-2.3291
Std Error	2.5726	1.8755	1.9993	2.2644	1.8024	1.1524
Z-Statistic	-0.3458	-0.3421	-0.3378	-0.4152	1.9685	-2.0211
P-Value	0.7295	0.7323	0.7355	0.6780	0.0490	0.0433
LEV						
Coefficient	2.6847	2.3729	1.0908	1.0663	0.0766	0.1223
Std Error	1.3235	0.6593	0.5704	0.6673	0.1441	0.0818
Z-statistic	2.0285	3.5991	1.9124	1.5979	0.5316	1.4946
P-Value	0.0425	0.0003	0.0558	0.1101	0.5950	0.1350
LIQTA						
Coefficient	-7.5440	-3.2972	-1.3323	-8.5594	-6.3965	-4.0194
Std Error	2.5832	1.6004	1.5267	2.7942	1.7168	1.1862
Z-statistic	-2.9204	-2.0602	-0.8727	-3.0633	-3.7258	-3.3886
P-Value	0.0035	0.0394	0.3828	0.0022	0.0002	0.0007
R_TA						
Coefficient	1.3460	-3.8008	-3.5019	1.5672	-1.7406	-0.2134
Std Error	1.8915	1.3315	1.0248	1.4412	0.8157	0.5614
Z-statistic	0.7116	-2.8546	-3.4170	1.0874	-2.1338	-0.3801
P-Value	0.4767	0.0043	0.0006	0.2769	0.0329	0.7038
LOGTA						
Coefficient	-0.5969	-0.5586	-0.5284	-0.4560	-0.8652	-0.1558
Std Error	0.2618	0.1980	0.2158	0.2419	0.2128	0.1277
Z-statistic	-2.2802	-2.8216	-2.4482	-1.8853	-4.0661	-1.2196
P-Value	0.0226	0.0048	0.0144	0.0594	0.0000	0.2226

Table 8.4 – Hotel & Restaurant Industry

Total Marginal Effects, Hotel & Restaurant Industry						
Variable	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Intercept						
Coefficient	0.7098	0.5872	1.8798	-2.0117	1.0366	0.0304
Std Error	1.9532	1.5848	1.9048	1.7379	1.2929	1.7426
Z-Statistic	0.3634	0.3705	0.9869	-1.1575	0.8017	0.0174
P-Value	0.7163	0.7110	0.3237	0.2470	0.4227	0.9861
LEV						
Coefficient	0.8795	0.6595	-0.0731	-0.0303	0.1031	-0.2381
Std Error	0.4118	0.2963	0.2967	0.2948	0.2500	0.0803
Z-statistic	2.1357	2.2253	-0.2465	-0.1028	0.4123	-2.9669
P-Value	0.0327	0.0261	0.8053	0.9181	0.6801	0.0030
LIQTA						
Coefficient	-1.1135	-4.5067	-1.1411	-2.3771	-8.7476	-2.8718
Std Error	1.2719	1.4996	1.1454	1.3939	1.9592	1.4130
Z-statistic	-0.8754	-3.0053	-0.9962	-1.7053	-4.4650	-2.0324
P-Value	0.3814	0.0027	0.3191	0.0881	0.0000	0.0421
R_TA						
Coefficient	-0.0416	-1.2892	-1.3346	-1.4845	-0.7270	-1.0898
Std Error	1.3460	1.1322	0.8898	0.9644	0.8001	0.6478
Z-statistic	-0.0309	-1.1386	-1.4999	-1.5393	-0.9087	-1.6824
P-Value	0.9753	0.2549	0.1336	0.1237	0.3635	0.0925
LOGTA						
Coefficient	-0.6708	-0.5296	-0.7416	-0.2395	-0.4906	-0.5327
Std Error	0.2367	0.1887	0.2391	0.2019	0.1534	0.2286
Z-statistic	-2.8342	-2.8074	-3.1019	-1.1865	-3.1982	-2.3306
P-Value	0.0046	0.0050	0.0019	0.2354	0.0014	0.0198

Table 8.5 – Transport Industry

Total Marginal Effects, Transport Industry						
Variable	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Intercept						
Coefficient	-1.2877	0.4892	-2.9986	-3.0221	-2.7347	-3.0682
Std Error	2.9952	1.9975	2.0951	2.5246	1.8295	1.7698
Z-Statistic	-0.4299	0.2449	-1.4313	-1.1971	-1.4948	-1.7336
P-Value	0.6672	0.8065	0.1524	0.2313	0.1350	0.0830
LEV						
Coefficient	7.5961	4.2082	5.3895	6.1838	2.8439	2.4518
Std Error	1.5385	1.3147	1.2184	1.4430	0.8007	0.6774
Z-statistic	4.9375	3.2010	4.4233	4.2855	3.5517	3.6195
P-Value	0.0000	0.0014	0.0000	0.0000	0.0004	0.0003
LIQTA						
Coefficient	-8.7362	-5.8887	-3.4093	-7.8942	-2.8278	-3.6024
Std Error	4.1789	2.3082	2.2831	3.6075	1.6607	1.9533
Z-statistic	-2.0905	-2.5512	-1.4933	-2.1883	-1.7027	-1.8443
P-Value	0.0366	0.0107	0.1354	0.0287	0.0886	0.0651
R_TA						
Coefficient	-1.4974	-0.0268	-1.1775	0.4520	0.9013	0.1851
Std Error	2.0937	1.6468	0.9125	1.5800	1.2368	0.8458
Z-statistic	-0.7152	-0.0163	-1.2904	0.2861	0.7287	0.2188
P-Value	0.4745	0.9870	0.1969	0.7748	0.4662	0.8268
LOGTA						
Coefficient	-1.0233	-0.8231	-0.5625	-0.6700	-0.3666	-0.3236
Std Error	0.3065	0.1941	0.1735	0.2295	0.1620	0.1674
Z-statistic	-3.3386	-4.2414	-3.2415	-2.9190	-2.2628	-1.9331
P-Value	0.0008	0.0000	0.0012	0.0035	0.0236	0.0532

Table 8.1-8.5 show the total marginal effects of the different financial ratios for the different industries. The tables also show the Z-statistics of these coefficients and the corresponding p-value.

Exhibit 9 – ROC Results

Figure 9.1-9.6 – ROC Curves for Models without Industry-Effect (IE)

Figure 9.1: Year 2006, No IE

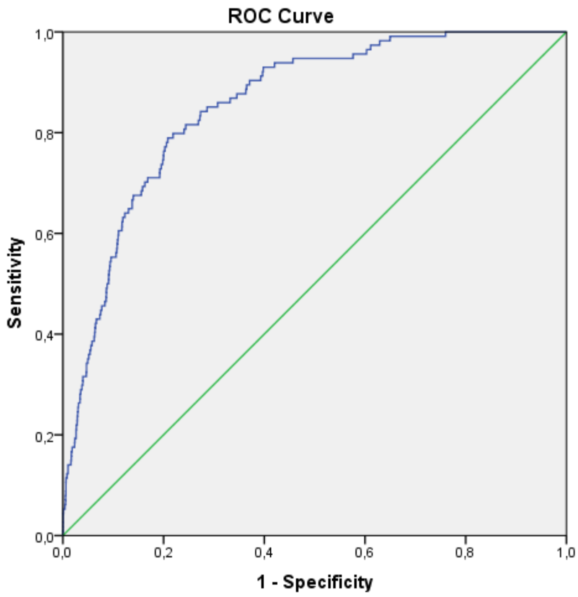


Figure 9.2: Year 2007, No IE

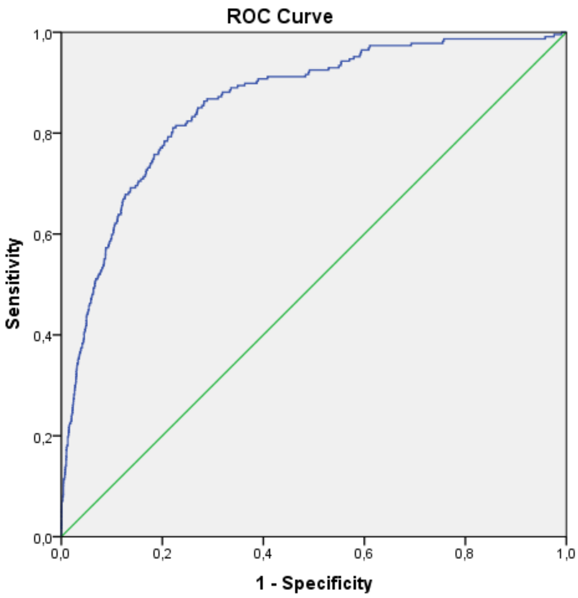


Figure 9.3: Year 2008, No IE

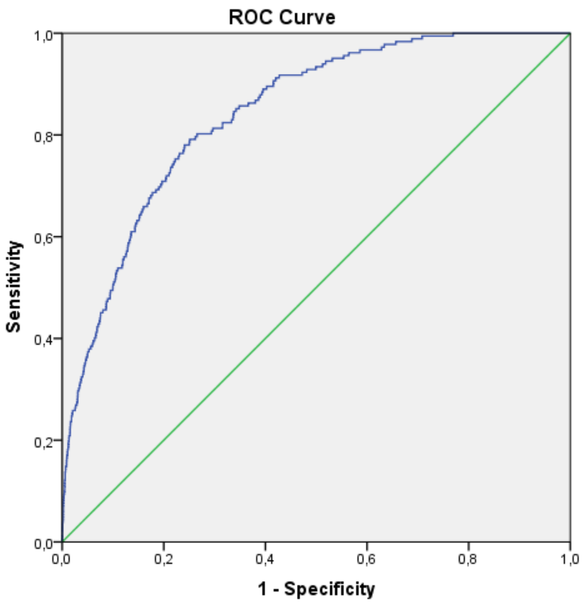


Figure 9.4: Year 2009, No IE

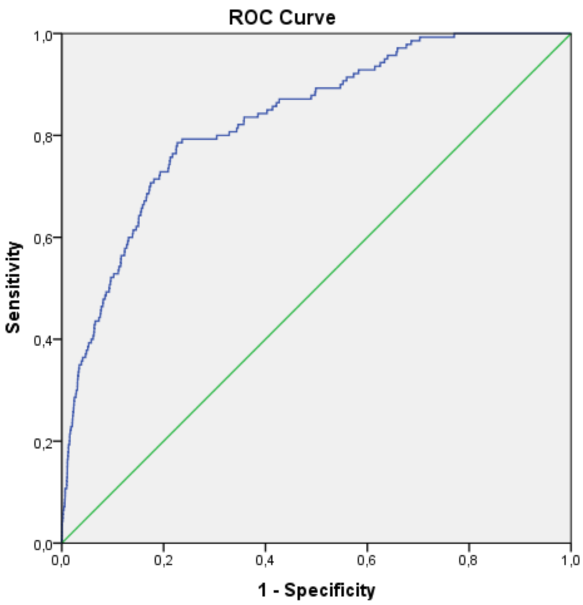


Figure 9.5: Year 2010, No IE

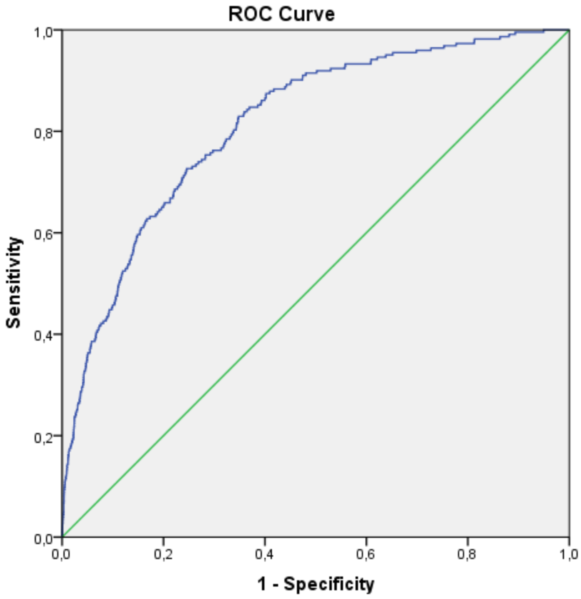
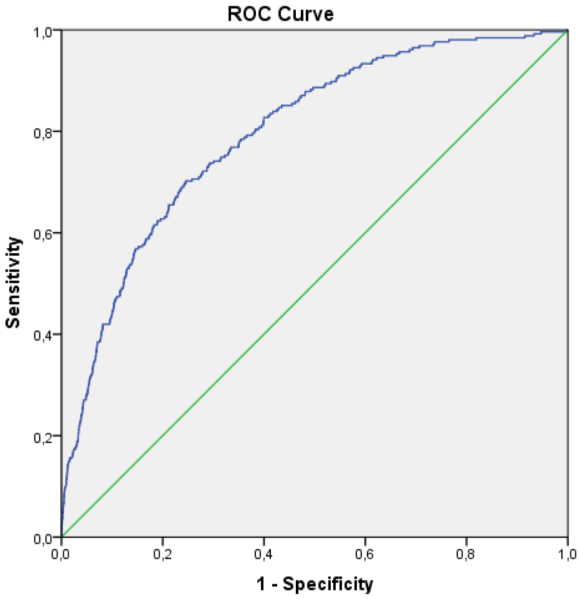


Figure 9.6: Year 2011, No IE



The figures show the ROC curves for the different models. These are based on the estimation sample.

Figure 9.7-9.12 – ROC Curves for models including Industry Effects

Figure 9.7: Year 2006, Incl. IE

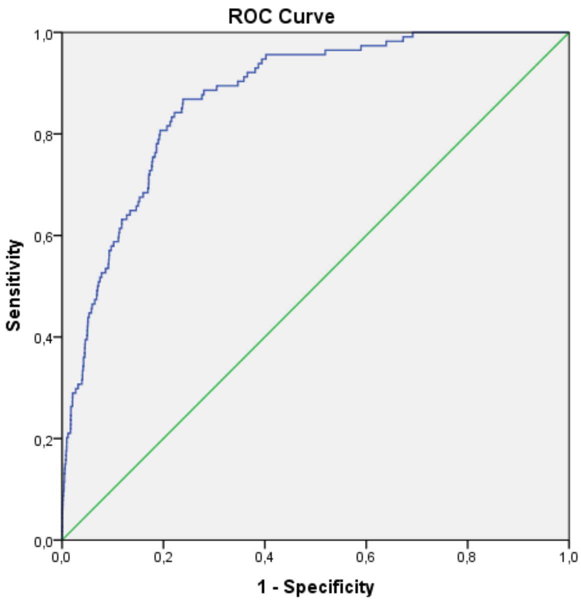


Figure 9.8: Year 2007, Incl. IE

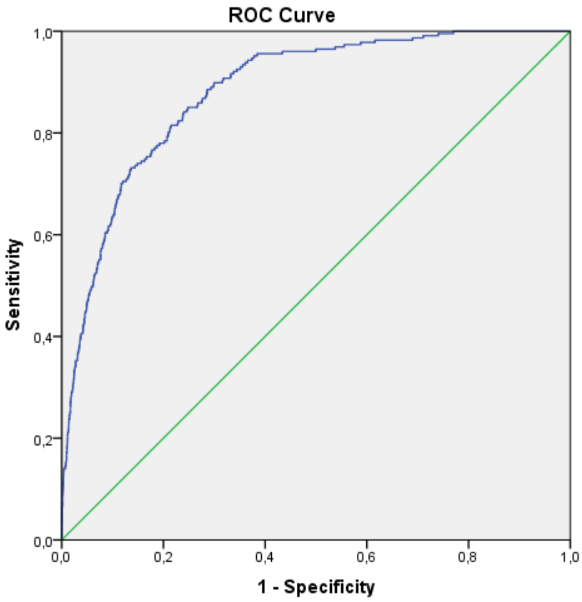


Figure 9.9: Year 2008, Incl. IE

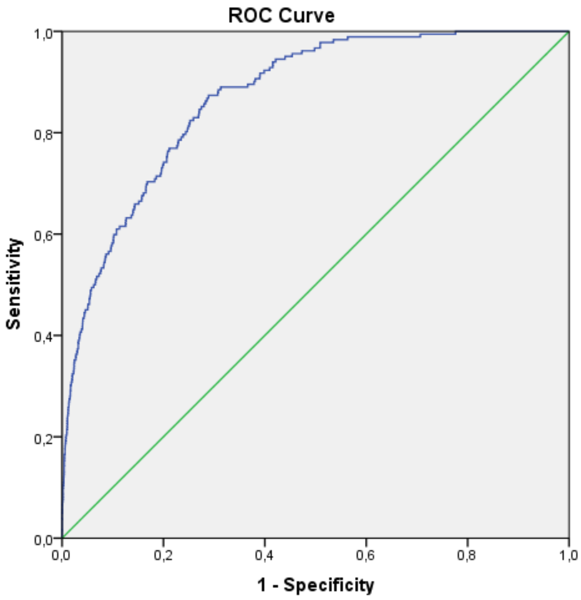


Figure 9.10: Year 2009, Incl. IE

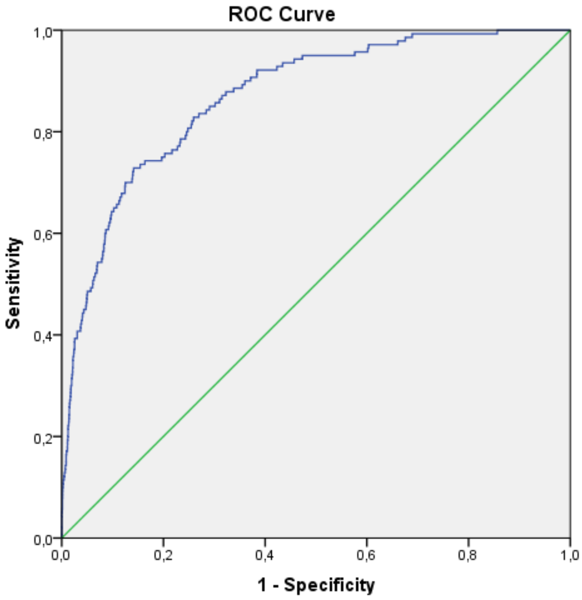


Figure 9.11: Year 2010, Incl. IE

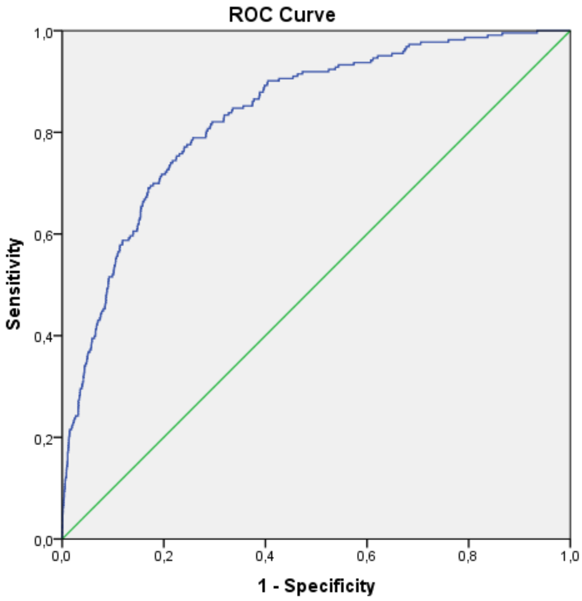
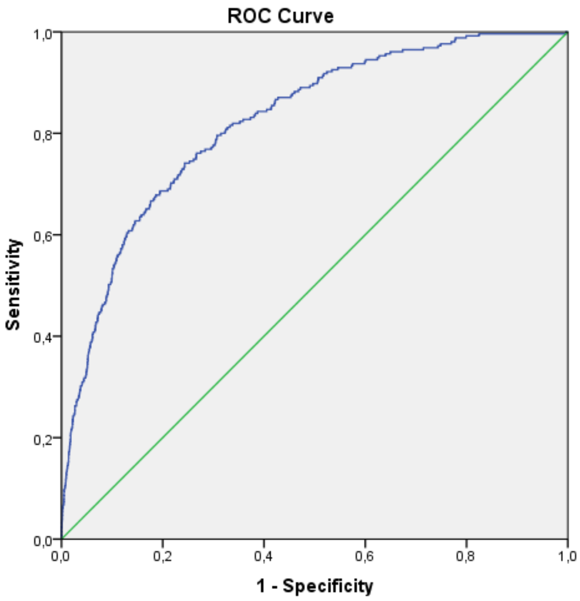


Figure 9.12: Year 2011, Incl. IE



The figures show the ROC curves for the different models. These are based on the estimation sample.

Table 9.1 – Areas under Curves on Estimation Sample

Test of AUC Equality between models on Estimation Sample					
Year		*No IE*	*Incl. IE*	*Z-Statistic*	*P-value*
2006	Area	0.856	0.873	-0.8285	0.2037
	Std. Error	0.015	0.014		
2007	Area	0.859	0.883	-1.4633	0.0717
	Std. Error	0.013	0.01		
2008	Area	0.843	0.871	-1.6442	0.0501
	Std. Error	0.013	0.011		
2009	Area	0.831	0.869	-1.6761	0.0469
	Std. Error	0.017	0.015		
2010	Area	0.814	0.835	-1.0992	0.1358
	Std. Error	0.014	0.013		
2011	Area	0.796	0.823	-1.4132	0.0788
	Std. Error	0.014	0.013		

The table shows the areas under the ROC curves when these are based on the estimation sample. The table also shows the results from equality tests between the areas of the two kinds of models.

Notes:

No IE = Model with no industry effects; Incl. IE = Model including industry effects.

Null-hypothesis: (AUC for model with no IE) = (AUC for model incl. IE)

Alternative hypothesis: (AUC for model incl. IE) > (AUC for model with no IE)

Table 9.2 – Areas under Curves on Holdout Sample

Test of AUC Equality between models on Holdout Sample					
Year		*No IE*	*Incl. IE*	*Z-Statistic*	*P-value*
2006	Area	0.816	0.834	-0.6356	0.2625
	Std. Error	0.021	0.019		
2007	Area	0.849	0.852	-0.1696	0.4327
	Std. Error	0.012	0.013		
2008	Area	0.842	0.863	-1.1389	0.1274
	Std. Error	0.014	0.012		
2009	Area	0.827	0.864	-1.6352	0.0510
	Std. Error	0.016	0.016		
2010	Area	0.806	0.817	-0.5556	0.2892
	Std. Error	0.014	0.014		
2011	Area	0.806	0.826	-1.1305	0.1291
	Std. Error	0.013	0.012		

The table shows the areas under the ROC curves when these are based on the holdout sample. The table also shows the results from equality tests between the areas of the two kinds of models.

Notes:

No IE = Model with no industry effects; Incl. IE = Model including industry effects.

Null-hypothesis: (AUC for model with no IE) = (AUC for model incl. IE)

Alternative hypothesis: (AUC for model incl. IE) > (AUC for model with no IE)

Exhibit 10 – Prediction Accuracy

Table 10.1 – Accuracy on Estimation Sample

Prediction Accuracy on Estimation Sample								
	Model without Industry Effects			Model with Industry Effects			Test of Equlity in Accuracy	
Year	*Sensitivity*	*Specificity*	*Prediction Accuracy*	*Sensitivity*	*Specificity*	*Prediction Accuracy*	*Z-statistic*	*P-Value*
2006	78.9%	78.9%	78.9%	80.7%	80.7%	80.7%	-4.53	0.0000
2007	78.9%	78.9%	78.9%	79.3%	79.3%	79.3%	-0.94	0.1745
2008	76.4%	76.4%	76.4%	77.5%	77.3%	77.3%	-2.41	0.0079
2009	77.1%	77.1%	77.1%	77.1%	77.1%	77.1%	0.00	0.5000
2010	73.5%	73.5%	73.5%	76.2%	76.2%	76.2%	-7.54	0.0000
2011	72.2%	72.1%	72.1%	74.5%	74.5%	74.5%	-6.99	0.0000
Avg	**76.2%**	**76.2%**	**76.1%**	**77.6%**	**77.5%**	**77.5%**		

The table shows a comparison between the two kinds of models on different measures of accuracy.

Note:

Null-hypothesis: Prediction accuracy for model without industry effects is equal to prediction accuracy for model including industry effects.

Alternative hypothesis: Prediction accuracy for model including industry effects is higher than the prediction accuracy for model without industry effects.

Table 10.2 – Accuracy on Holdout Sample

Prediction Accuracy on Holdout Sample										
	Model without industry effects				Model with industry effects				Test of Equlity in Mean of Sens. & Spec.	
Year	*Sensitivity*	*Specificity*	*Mean of Sens. & Spec.*	*Prediction Accuracy*	*Sensitivity*	*Specificity*	*Mean of Sens. & Spec.*	*Prediction Accuracy*	*Z-statistic*	*P-Value*
2006	68.6%	79.1%	73.9%	79.0%	67.6%	80.7%	74.2%	80.6%	-0.72	0.2355
2007	75.5%	79.0%	77.3%	78.9%	75.1%	79.5%	77.3%	79.4%	-0.13	0.4476
2008	70.9%	76.3%	73.6%	76.2%	79.1%	76.7%	77.9%	76.7%	-11.19	0.0000
2009	74.8%	77.7%	76.3%	77.7%	78.3%	77.4%	77.9%	77.4%	-4.42	0.0000
2010	69.5%	74.5%	72.0%	74.4%	72.1%	76.7%	74.4%	76.6%	-6.63	0.0000
2011	76.1%	72.6%	74.4%	72.7%	73.3%	75.6%	74.5%	75.5%	-0.30	0.3820
Avg	**72.6%**	**76.5%**	**74.6%**	**76.5%**	**74.3%**	**77.8%**	**76.0%**	**77.7%**		

The table shows a comparison between the two kinds of models on different measures of accuracy.

Note:

Null-hypothesis: Mean of sensitivity and specificity for model without industry effects is equal to the mean of sensitivity and specificity for model including industry effects.

Alternative hypothesis: Mean of sensitivity and specificity for model including industry effects is higher than for model without industry effects.

Kan konkursprediktionsmodeller förbättras med industritermer?

Denna fråga ställde vi oss innan vi satte igång att undersöka cirka 317 000 årsredovisningar från 2006 till 2011. Trots alla anpassningar visar resultaten endast på marginella förbättringar.

Den ekonomiska krisen har drabbat Europa och Sverige hårt de senaste åren. Många företag har sett minskande försäljning och för vissa har den enda utvägen varit en konkurs. Konkurserna och företagsproblemen har ökat och är något som bland annat bankerna har märkt av.

Behovet av konkursprediktionsmodeller kan tyckas extra stort på grund av denna kris och var ett motiv bakom vår studie. Om modellerna kunde förbättras kanske konkurserna kunde skapa mindre problem i samhället?

En känd modell för konkursprediktion är Altmans klassiska Z-scoremodell från sextiotalet. Denna modell skapade ett nytt studieområde som sedan dess har kompletterats med liknande redovisningsbaserade modeller. En annan känd modell är Mertons kreditriskmodell från sjuttiotalet som bygger på optionsteori. Denna modell är dock lättast att använda på börsnoterade företag.

Vid studiens inledande ansåg vi det vara ett problem att existerande redovisningsbaserade modeller i liten utsträckning tar hänsyn till vilken bransch ett företag tillhör. Olika branscher ser ut på olika sätt, med olika kapitalstrukturer och lönsamhetsstrukturer. Det vore därför inte orimligt om också nyckeltal varierar mellan industrier i sin förmåga att förutspå konkurser.

Ett omfattande arbete tog därför vid där hundratusentals årsredovisningar från svenska onoterade aktiebolag samlades in. I slutändan undersöktes cirka 317 000 årsredovisningar från åren 2006 till 2011. Olika nyckeltal samlades också in.

Syftet med undersökningen var dels att testa hur modellerna kunde förbättras med industrianpassningar men ett annat syfte var också att undersöka hur nyckeltalens prediktionsförmåga skiljer sig mellan fem utvalda branscher: Bygg- och design, detaljhandel, hotell och restaurang, tillverkning, och transport.

Våra resultat visar att modeller med industrianpassningar endast marginellt ökade klassificeringsförmågan på vår testgrupp med företag. I vår analys lades lika stor vikt vid andelen rättklassificerade konkursföretag som friska företag vid val av avskärningsvärden. Med detta antagande som grund kunde våra modeller med industritermer i tre av sex fall visa på en statistiskt säker ökning i prediktionsförmåga.

De blandade resultaten pekar på att många faktorer påverkar en modells prediktionsförmåga, varav valet av avskärningsvärde är en. En annan faktor visade sig vara tiden. De uppskattade modellerna visade sig skilja mycket mellan åren. Att uppskatta en modell för att sedan använda den på finansiell data från andra år kan därför ifrågasättas.

”Man kan ifrågasätta användandet av många variabler”

Att studien visade på så pass små skillnader i prediktionsförmåga mellan de två typerna av modeller som vardera innehåller 5 respektive 25 koefficienter gör att man kan ifrågasätta användandet av många variabler i en sådan modell. Vi drar slutsatsen att industrianpassningen visserligen ökar prediktionsförmågan en aning men att ett fåtal variabler räcker mycket väl för att skatta ett företags konkursrisk.

Av David Lundqvist och Jakob Strand