Prediction of Corporate Bankruptcy

of Private Firms in The Netherlands

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Coach Dr. Mathijs van Dijk (Financial and Economic Management)
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Abstract

This paper tries to deal with predicting corporate failure. It describes the conception of a construct to predict bankruptcy of relatively small sized, private companies in The Netherlands.

Plentiful research, study and discussion have taken place on public companies. Private companies largely have been ignored because of the difficulty of obtaining information. Until now…. The fact that research on this subject is mostly done on public companies is regretful since it usually concerns large(r) companies, whereas business failure in general is a more common phenomenon among smaller – usually private – companies. Being able to predict business failure – obviously – is a most interesting matter for all suppliers of credit, in any form.

This thesis basically replicates the research described in a number of highly esteemed papers by Edward I. Altman, William H. Beaver, Marc Blum, Robert O. Edmister and James A. Ohlson. As put before, most of these studies are done on public companies because accounting-based data for these companies are readily available. This study is able to conduct – unprecedented – research on small, privately owned companies in The Netherlands because the data needed to do so are made available.

The goal of this study is to prove the validity of the statement that *financial ratios are useful to predict business failure of small, private firms in The Netherlands.* By combining several strong points of the previously mentioned studies, this study is expected to achieve high scoring results. This is the case because the available data are stratified for company size and industry type and so to control for industry differences, the use of hold-out samples and subsample validation of the statistical model used.

A thorough evaluation of the literature is followed by a careful analysis of methodologies that are available to perform the statistical tests. Multiple discriminant analysis, a linear discriminating technique, is chosen as the method to do the analysis of the data.

The results of the statistical tests lead to acceptance of the main hypothesis. The outcome of this thesis is consistent with previous studies although it turns out to be less pronounced and less thrilling as hoped for. On the other hand the results of this thesis have a more practical value since the most important reason for less discriminating power – the exact matching of pairs – is a painstaking exercise which makes it very difficult to use in practice.

As always, there is room for improvement. The study will conclude with recommendations for further research.

1 Introduction

1.1 Introduction

It is all about the money. Small or large companies, private or public, they don't run without funds. Even for not–for–profit companies, the bills will have to be paid or suppliers will stop supplying and the business will be unable to continue.

At a point where there are insufficient means to continue the business, the management will have to liquidate the company's assets, pay or repay its debtors and walk away with the remains, if any. In case there are insufficient funds to repay all debtors in full, the company, at some point in time, will be declared bankrupt. A curator will liquidate the assets and distribute the remaining financials to the debtors in the rightful order. In both cases the company will cease to exist. If there are debtors left unpaid in full and management is to blame for mismanagement, legal prosecution will most likely follow.

It is important to be able to predict corporate failure. Think of a credit manager at Fortis that has to decide whether to grant a small, private firm in The Netherlands additional credit to renew its machine park. A bad loan won't add to the bank's profitability nor will it to the bank managers' reputation. It will be of great help to the bank manager to have a model available that will help to make a well-judged call. The same applies when we intend to become a customer of a company that will be supplying goods and / or services that are of strategic importance to us. It is essential that we make sure that the business will last.

Credit risk or default risk concerns the financial state a company is in. An assessment of a company's financial condition enables us, within certain boundaries, to establish what the future may have in store for it, and by doing so to determine the risk of doing business with that company. Credit risk measurement has evolved dramatically over the past 20 years. The development has been caused by a structural, worldwide increase in the number of bankruptcies[1], a trend towards disintermediation, more and more intensive competition, a decline in value of real assets (and so collateral) and a large growth of off-balance sheet instruments (swaps, options, forwards, futures et cetera) with inherent default risk exposure. The question arises how credit risk may be determined. Is it about financial ratios, about share prices and thus market value of assets compared to book value of assets, or is there more to it?

Some 20 years ago most financial institutions relied almost exclusively on subjective analyses or so–called banker 'expert' systems to assess the credit risk on corporate loans. Essentially, bankers used information on various borrower characteristics such as borrower character (reputation), capital (leverage), capacity (volatility of earnings) and collateral, to reach a largely subjective judgment (i.e., that of an expert) as to whether or not to grant credit. These were the so-called 4 C's of credit. Many – more objectively based – approaches to quantify default risk have been developed and refined ever since.

[1] Global Macroeconomic and Insolvency Outlook 2007 (Euler Hermes, Datastream, Eurostat)

Amongst these are at least 4 multivariate accounting-based credit-scoring models: the linear probability model, the logit model, the probit model (*prob*ability un*it*) and the discriminant analysis model. Of these, the discriminant analysis model is most commonly used.

The so-called logit analysis predicts the probability of borrower default, assuming that the probability of default is logically distributed. Well-known discriminant analysis models are the ZETA® credit risk model (Altman, Haldeman and Narayanan, 1977), consisting of 7 variables, and Altman's earlier, 5 variables model. While the multivariate accounting based credit-scoring models have shown to perform quite well, they have also been the subject of some criticism. One argues that accounting information is only measured at discrete intervals, that the models may fail to pick up subtle and fast moving changes in borrower conditions and that the world is mostly non-linear, so why should linear discriminant analyses and linear probability models accurately explain its variables?

Risk of ruin models like the Black-Scholes-Merton model (1976), Black and Scholes' OPM (Option Price Model, 1973) and the KMV model (1993) have gained increasing credibility. These models use the volatility of the market value of the firm's assets to indicate bankruptcy.

Other capital market based models are Altman's mortality rate model (1988, 1989) and the aging model by Asquith et al. (1989). These models use past data on bond defaults by credit grade and years to maturity. Credit rating agencies like Moody's and Standard & Poor's have adopted and modified the mortality rate approach. They provide investors and financial professionals objective and credible market intelligence.

Finally, a newer approach is the application of neural network analysis to the credit risk classification issue. Neural network analysis is based on non-linear discriminant analysis. This type of analysis drops the assumption that variables which are used to predict bankruptcy are linearly and independently related.

All in all it appears that most methods to ascertain credit risk use the variability in the market value of a firm's assets based on the company's share price or the development of its share price. Successive literature on bankruptcy and credit risk has built upon early and important works of Beaver (1966) and Altman (1968). Notwithstanding all these long and numerous efforts, fully satisfying bankruptcy prediction models have not yet been obtained. The question how investors or banks may ascertain the risk to lend money to companies that are in need of capital, remains an interesting one. What are the chances that things will turn out the wrong way and in the end leave investors empty-handed?

Bankruptcy prediction is a concern for the various stakeholders in a firm: owners, managers, investors, creditors and business partners. But also of government institutions that are responsible for maintaining the stability of financial markets and general economic prosperity. The subject of this thesis is relevant for all suppliers of working capital: banks, private investors, business angels, venture capitalists et cetera, who wish to minimize chances that they will lose money, but also for services suppliers such as lawyers and accountants. These may wish to make sure that companies they intend to do business with, or, are doing business with, will be there for the long run. They will need to do so in order to determine the risk of damage to their corporate image or the risk of lawsuits and consequent damage claims. This may be so as a result of getting involved in a straightforward bankruptcy of one of their clients, but more likely in case of a bankruptcy caused by mismanagement that will turn into a scandal.

1.2 Goal of This Study

Default risk is the uncertainty surrounding a firm's ability to fulfill it debts and financial obligations. While this statement has a certain logic, it leaves some commonsense questions unanswered. First, how do we measure failure to meet financial obligations? Second, how do we measure the probability that a firm will fail to meet its debts and financial obligations? Answering these questions will lead to an empirical measure of financial distress. *The purpose of this study is to test the usefulness of financial ratio analyses for predicting small, private business failure in The Netherlands*. It will continue the large amount of research that has been done in this field on public companies. Many researchers have advanced empirical studies of financial analyses by applying statistical techniques to financial data of firms that went into bankruptcy and firms that appeared successful. However, these studies have been done mostly on listed companies of which financial information, or part of it, is readily available by deducting it from the prices of their shares that are traded on a security exchange on a daily basis. The research indicates that analysis of selected financial ratios is useful for predicting failure. However, private businesses – usually synonym for small companies – have largely been ignored because of the difficulty of obtaining data. Doing research on companies of which information is relatively easy to obtain, consequently, is the obvious choice. It does not, however, take away the yearn for more insight on the issue in relation to private companies. It is rather peculiar that hardly any research has been done on private companies. The more so since the vast majority of companies is privately owned. This study will carry on this previous research but focus on private or non-public companies instead and therefore will be a valuable contribution to the existing literature on the subject.

Another interesting question emerges: *Does the security market do a better job at predicting chances of default than financial ratio analyses do?* This concerns the efficient market (Fama 1960), where securities are traded for prices which are supposed to reflect all information about the issuer. The market that can't be beaten and thus implies to have the right answer when it comes to credit risk? The capital market theory and capital asset pricing model (CAPM by William Sharpe, 1964) claim to reflect the risk of default probability by the spread over the default-free rate of interest to compensate lenders for this uncertainty. Recent work of Arnott, Hsu, Liu and Markowitz (2007), however, suggests that there is noise in stock prices in a sense that the price of a stock can be randomly different from its intrinsic value. This assumption undermines the efficient market hypothesis. The so-called dot-com bubble illustrates this quite well. The speculative bubble was covering roughly 1995 to 2001 with its climax in 1999. During this period stock markets in Western nations saw their values increase rapidly because of growth in the Internet sector and related fields. There were record-setting rises in stock valuation. Stocks were dramatically overvalued in a self-perpetuating boom.

1.3 Setup of This Study

This study looks at the relation between accounting-based variables and the chances of default of Dutch, privately-owned companies. To the author's knowledge, no research in this field, (specifically on Dutch, non-public companies) has been conducted thus far. While the focus may seem narrow, its application is broad in the sense that the methodology is applicable to public companies as well as to companies in any geographical market other than The Netherlands.

To start off, the phenomena to be researched need to be defined: failure to meet debts and financial obligations and the probability to fail to meet debts and financial obligations. The data, the accounting-based variables from a 5 year sample period from 2002 to 2006, of 400 to 800 failed as well as 400 to 800 non-failed companies, are obtained from the archives of Graydon Credit Management Services. This approach is known as an archival study. Archival studies are a widely used method in empirical corporate finance research.

Next, the obtained data need to be converted into the appropriate liquidity, profitability and solvability ratios. Finally, a (linear) relation between the dependent or to-be-explained variable 'bankruptcy' (a logistic variable that may take 0 [not bankrupt] or 1 [bankrupt] as value) and multiple variables *total debt / cash flow*, *net income to total equity* (both profitability measures), *total equity to total assets* (a solvency or leverage measure), *working capital to total assets* and *current assets to current liabilities* (both liquidity measures), will be ascertained. The data are analyzed using a multiple discriminant analysis (MDA).

The structure of this thesis is as follows. Chapter 2 starts off by giving a chronological overview of the many theoretical contributions with regard to credit risk modeling. In this chapter a considerable number of articles and studies will be summarized and advantages as well as disadvantages will be pointed out. Chapter 3 will zoom in on a large array of variables that may be used to construct a model in order to establish credit risk.

In the 4th chapter, the theory and literature consequently come together resulting in the propositions for this research paper. It provides an overview of the methodology which is applied to the used analyses. Tight hypotheses are posed and will be tested by the empirical results obtained by this archival study.

Chapter 5 describes the data set, how it has been obtained precisely and prepared to do the statistical analyses. Chapter 6 contains the empirical results which are derived from the statistical analyses of the entire data set.

Although the methodologies to establish the chances of corporate default is a generally accepted and an approved framework in the field of finance, some limitations are apparent. One of them being applying existing models to private companies. I am aware of some of these limitations and will be discussing them in chapter 7 (conclusions and recommendations).

This thesis concludes with the implications of the results and recommendations for further research on credit risk.

1.4 Concluding Comments

Now we have set the scene in which this study will come to maturity, we are ready to proceed to chapter 2 which starts off by giving a sequential overview of the many theoretical contributions with regard to bankruptcy prediction modeling.

2 Business Failure Measurement Through Time

2.1 Introduction

Accurate business failure predictions are of great interest to various parties; academics, regulators, insurers, factors, forecasters of corporate mergers and financial analysts in general. Academics use bankruptcy prediction to test various matters of interest. One of these, for instance, is trying to ascertain whether bankruptcy risk is priced in stock returns. Regulators are interested in forecasting models to be able to monitor the financial health of banks, pension funds and other institutions. Forecasters of corporate mergers are interested because unhealthy firms are often considered a takeover target. For the purpose of speculating on the increase in value of the unhealthy take-over target and decrease in value of the party that takes over (merger arbitrage). And general financial analysts use default forecasts – among other things – to price corporate debt. They all use similar methodologies to predict corporate failure. Given the broad interest in bankruptcy prediction an accurate forecasting technology is most valuable.

Business failure and bankruptcy, (economic failure, insolvency, ruin), are defined as a legal or natural entity that is forced to cease doing business because it is unable to fulfill its obligations as they mature. Operationally a firm is said to have failed when bankruptcy, bond default, overdrawn bank account or nonpayment of any kind, has occurred. Default literally means failure to pay, usually a state just prior to, and mostly leading to, bankruptcy. In this paper all these terms are used interchangeably.

This chapter traces the developments in credit risk measurement literature over the past 40-odd years (1966 to 2006). It illustrates the evolution of the literature about credit risk measurement by discussing through time, articles that take a different view on the matter and articles that are considered important contributions to shed wisdom on the subject. Methods described vary and each study places emphasis on a different part of the subject they all have in common, bankruptcy prediction. Some also differ entirely from the method to predict bankruptcy, eventually used in this paper. Yet, they are still discussed because they complete the overall picture, as far as view on the matter and methodology are concerned as well as the developments of both through time.

2.2 Univariate Estimation

William H. Beaver's 'Financial Ratios as Predictors of Failure', which was published in 1966, is regarded as one of the classic studies in the field of Credit Risk Measurement. Ratio analysis began – as early as 1923 – with the development of a single ratio, the current ratio, for a single purpose: the evaluation of credit-worthiness. The current ratio (the quotient of current assets and current liabilities) indicates the ability of a company to fulfill its short term (within-one-year) obligations. Beaver's article is a formal, empirical verification of the usefulness of ratios as a predictor of failure.

Beaver encountered a significant problem, namely, the unavailability of accounting data of failed firms. The only source available excluded non-corporate, privately held companies and non-industrial firms (such as utility companies, transportation companies and financial institutions). The choice for the population anyway was admittedly a reluctant one as the probability of failure among this group of firms is not as high as it is among smaller firms. In this sense it was not the most relevant population upon which to test the predictive ability of ratios. In terms of invested capital, however, it represented over 90% of the total contributed by investors and creditors. So, not a trivial group.

Beaver selected a group of 79 failed companies that were a heterogeneous group in terms of asset-size and industry type. The selection of non-failed firms were paired with the failed firms. That is, the same asset-size and industry type was selected. The paired-sample design was used to prevent differences in asset-size and industry to blur the outcome.

Beaver collects the data from the financial statements of up to 5 years before failure. The year of the non-failed companies' statements is selected to match the year of the statements of the failed companies. For every set of financial statements available, 30 ratios are computed. In selecting the ratios, each ratio is to add as much additional information as possible. Common elements are to be reduced to a minimum. The analysis of the data comprises a comparison of the mean values, a dichotomous classification test, and an analysis of probability ratios. The comparison of the means values is not meant as a predictive test but as a convenient way of outlining general relationships between failed and non-failed companies. A downside of this test is that it concentrates on the mean of the ratios only; it does not reveal how large the difference between a ratio of a failed and a non-failed firm is. The dichotomous classification test (failed [Yes] or [No]) predicts the failure status of a firm based solely upon the financial ratios. Each ratio of each company, failed and non-failed, is arrayed (put in ascending order) and an optimal cutting off point is established above or below which the misclassifications of failed or non-failed are the least. The test clearly illustrates the percentage misclassifications per ratio, per year prior to failure. A limitation of this test is that it treats the prediction dichotomous while a ratio very far away from the cutoff point may be given more confidence to the prediction than one that is close. This additional information from the ratio is not revealed in this test. Also, as noted by Blum (1974), there is not necessarily a unique cutoff point. More than one may be optimal and most probably will be giving different results. Different cutoff points in different years prior to failure therefore produce inconsistent predictions. The probability study of failure indication by ratios is essentially a Bayesian approach. It assesses the probability of failure conditional upon the value of a ratio. Beaver's approach misclassified only 13% of the sample firms 1 year before bankruptcy and 22% of the sample firms 5 years before bankruptcy.

Beaver was not so much looking for a way to predict corporate failure. Instead he set out to establish the usefulness of ratios in addressing accounting issues in general. While doing so he concludes that accounting data imply a definite potential to make predictions about company failure. In a later study of

Beaver, ‘Market Prices, Financial Ratios and the Prediction of Failure’, he finds that market-value variables and financial ratios are equally reliable.

2.3 Multivariate Discriminant Analysis

Altman’s 1968 article – in terms of purpose – is similar to that of Beaver (1966). Altman however, improves Beaver’s univariate study (analyzing one dependent variable at a time) by introducing the multivariate approach which allows for simultaneous consideration of several variables in the prediction of failure. Altman claims that univariate ratio analysis is susceptible to faulty interpretation. For instance, a firm with a poor profitability and / or solvability record may be regarded as being potentially bankrupt. However, because of its above average liquidity, the situation may not be that bad at all. Altman was the first to apply a multiple discriminant statistical methodology known as linear discriminant analysis (LDA) to develop a business failure prediction model. The methodology attempts to derive a linear relation from ratios that best discriminates between 2 groups, failed and non-failed.

Altman selects 2 groups of 33 companies. Of these, 1 group has gone bankrupt and 1 group is still in business. In terms of asset-size and industry the groups are not homogeneous. Altman also chooses a paired sample as far as asset-size, industry type, and period of reporting are concerned. Initially a list of 22 potentially helpful ratios is compiled based on popularity (by financial analysts) and relevance. Finally, 5 are selected as doing the best job predicting corporate failure. The choice of ratios is based on evaluation of inter-correlation and best result of numerous computations: working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to book value of total debt and sales to total assets. The complete discriminant function with these ratios incorporated leads to Altman’s Z-score model which – with 2 more ratios added – is called the ZETA® model. It appears the models have proven to be of value since both models today are still widely used by analysts throughout the world. Altman takes great care to make sure the methodology he uses is appropriate and that the model he has constructed contains the right ratios. To do so he tests the relative contribution to the total discriminating power of the function of the variables he has chosen and the overall discriminating power of the model by means of an f-test. He tests the predictive accuracy of his model by testing the whole range of predictors up to 5 years prior to failure. The predictive ability of his function on the 66-firm sample 1 year before failure is 79%.

Altman closes with several suggestions where and how to apply his model and that he recognizes at least one limitation being that his study examines publicly held manufacturing companies only for which comprehensive data were available, including market price quotations.

2.4 Rigorous Validation and Pairing

Blum is concerned about the accuracy of the methods to predict corporate bankruptcy thus far presented. His Failing Company Model (1969) is constructed specifically to aid in assessing the probability of business failure in antitrust merger cases. The interests are for real. The predictive accuracy of the Failing Company Model is evaluated by discriminant analysis. Blum's 1974 study reports on the results, the sturdiness, of the discriminant analysis. The sample set comprises 115 failed firms, paired with the same amount non-failed firms. The pairing criteria are asset size, industry type, sales, number of employees and fiscal year. The model distinguishes between failing and non-failing companies with an accuracy of 94% when failure occurred within one year of the prediction, 80% in case of 2 years and 70% in case of 3, 4 and 5 years from the year of prediction. Blum claims reliability of his model because of the choice of its variables, a precise pairing procedure and a rigorous validation procedure. Validation is accomplished by splitting the population in half, deriving the discriminant function from 1 half and testing it on the other, fresh half. Also replications of subsets of the original sample are tested. In order to establish whether the results are not obtained by chance only, statistical significance of group differences ([failed] and [non-failed]) can be tested by an F-test.

2.5 Trend Analyses

Edmister (1972) realizes that bankruptcy is a more common phenomenon around small companies. He analyzes the usefulness of financial ratio analysis for predicting *small business* failure. Beaver's, Blum's and Altman's studies indicate that the analysis of selected ratios is useful in predicting failure of medium and large asset-size firms. They have largely ignored small businesses because of the difficulty of obtaining data.

Edmister's small business failure function fails to discriminate when analyzing only 1 financial statement (what he calls the mono-annual sample) whereas Altman (1968) and Beaver (1966) show that one financial statement is sufficient for a highly successful discriminating function for large businesses. Edmister concludes that his discriminant function demonstrates an ability as good as Altman's and Beaver's provided that at least 3 consecutive financial statements are available for the analysis of a small business (what he calls the tri-annual sample).

Besides ratio levels Edmister uses a 3-year trend of each ratio as a predictor of small business failure. Previous empirical studies by Blum (1969), Merwin (1942) and Smith (1935) find that trends of some ratios lead to business failure. Businesses that are 'going the wrong direction' are viewed with greater caution than those whose trends are improving. A trend is defined as 3 consecutive years in which a ratio moves in one direction: up, down or staying level. Also 3-year averages of ratios, industry-relevant trends and industry-relevant levels are considered and found to be useful as predictors of (small) business failure. Averaging is expected to smooth the ratios and result in a more representative figure than calculated from only the most recent statement.

A summary of the ratios that are included in the 3 empirical studies of Beaver, Altman and Blum is presented in table 1. These studies show that only a few ratios can be combined to make a discriminant function with a high degree of reliability when applied to data from which the function is determined.

Although some ratios are found to be good predictors in more than one study, not one group of ratios is common to the 4 studies (this one included). This implies that the discriminant functions can be applied reliably only to situations very similar to those from which the function was generated.

Table 1

Summary of ratios found to be significant predictors of business failure in various empirical research [(I)]

	Researcher		
Ratio	**Altman ('66)**	**Beaver ('68)**	**Blum ('69)** [(II)]
Net Working Capital / Total Assets	√		√
Debt / Total Assets [(III)]	√	√	
Total Assets Turnover	√		
Net Operating Margin	√		
Earnings After Taxes / Total Assets		√	
Market Value of Equity / Book Value of Total Debt	√		
Cash Flow / Total Debt		√	√
Trend Breaks of Net Quick Assets / Inventory			√
Net Quick Assets / Inventory			√
Rate of Return to Common Shareholders			√

[(I)] The studies varied in purpose and scope; reference is made to the text for discussion of the definition of failure and population studied in each case.

[(II)] The 12-variable function was estimated for many time periods and the results varied widely. These 5 variables generally performed best over all of the time period.

[(III)] Defined as Debt / Net Worth in some studies.

Source: Edmister (1972)

2.6 Risk of Default and Company Value

The majority of research on bankruptcy focuses on the risk and cost of default from a creditors point of view. The impact of default risk on the value of a company's securities is given little attention. Arbel et al (1977) investigate the impact of bankruptcy in terms of the capital asset pricing model (CAPM). They seek to determine whether default risk is another, independent factor that determines common stock prices in addition to the market-related risk. Their study indicates that there are reasons to believe that the presence of default risk causes investors to demand a risk premium on firms with increased risk of bankruptcy, on top of the premium that is associated with the firm's level of market determined risk alone. The authors build a new linear programming model that enables them to isolate the premium on stock prices that is associated with default risk. They base their ideas on the capital market theory which suggests that default risk of a firm may be viewed as having 2 parts: the security's systematic risk and its unsystematic risk. The unsystematic risk may be diversified away by the investor. That is, by dividing investment funds among a variety of securities with different risk, reward, and correlation statistics so as to minimize the risk of losing out. The firm characteristics that are relevant to security valuations are assumed to be those embodied in the beta. The question is whether all the relevant bankruptcy risk is captured by the beta.

Arbel's research comprises data from CRSP (Center for Research in Security Prices) for the period of 1965 to 1973. Bond ratings for unsecured debt and ratings of unsecured debt are selected to provide an approximation of default risk of 223 companies. The authors develop a linear programming model to separate the effect of default risk. Their test results support the usefulness of the capital asset pricing model but suggests that the extent of cost of default when combined with the probability of occurrence is insignificant as an independent variable in generating stock returns. So, even though the suggestion seems logical and an interesting enough subject to examine, one has not been able to establish results of any significance with respect to the influence of default risk on the value of company securities.

M.J. Gordon (1971) raises some questions about the implications of financial distress to the value of a corporation too. What happens to the value of the common equity and the debt as a company falls into financial distress? And, is the value of a company in financial difficulties different or the same as the same company without the financial structure that is partially or in whole, responsible for its financial distress? Put in another way, does financial stress influence a firm's ability to finance its activities in various ways and through various sources, and what are the attitudes of the money providers towards the company and the existing stockholders and bondholders towards the money providers?

Apart from a theoretical explanation Gordon provides evidence on what happens on the value of a firm when it experiences financial distress by studying the changes in security values of 4 railroad companies in the period of 1966 to 1970. He finds out that in the distress period the market value of the company as well as the value of debt drops to roughly one third of its value prior to distress. Again theoretically, he establishes that the maturity schedule of a firm's debt and the amount of its non-operating liquid assets determine the firm's distance to default. The value of a firm and in particular the value of its common stock are reduced by increased risk and so he concludes, financial structure is of some concern to its stockholders.

2.7 Large Sample Estimation

In research on bankruptcy probability, methods are diverse and sample sizes relatively small. The sample sizes range from 13 (Stoškus, 2007), to 27 (Moyer, 1977) to 53 (Altman, 1968), to name but a few. Ohlson's study (1980) relies on observations from 105 bankrupt firms and 2,058 non-bankrupt firms. Although the aforementioned studies differ from this one as far as methodology is concerned (multiple discriminant analysis versus the logit model), it is nevertheless interesting and useful to compare their results with the ones from this study to see if sample size matters. A comparison of the previously mentioned studies and Ohlson's study indicates that error rates of the latter – even though he uses a large sample – are higher: approximately 10 percent versus approximately 5 percent. Some of the potential sources that may account for the difference are as follows. The first one is whether data is used from statements before bankruptcy or after. This study omits statements from after bankruptcy. Indeed, a number of companies is classified correctly additionally if these statements are used. Timing with regard to data and model seems to be of importance. Altman's 1968 study reports a misclassification rate of approximately 5 percent of failed firms. Altman and McGough (1974) apply that same model – developed in 1968 – to data of 28 firms that failed during the period 1970 – 1973. This effort yields a misclassification rate of 18%. This is a substantial and significant increase. Later, Altman, Haldeman and Narayanan (1977), rework what Altman did in 1968 using data from 1969 – 1975. The development of their ZETA® model includes a number of refinements in the utilization of discriminant analysis, as well as in the computation of financial ratios. Following from these refinements they report classification results of over 98%. Again, the results are better than the results from this study utilizing an exceptionally large sample size. Altman et al do not disclose the details of their ZETA® model since it is proprietary information. Moyer (1977) reexamines Altman's 1968 model using data from the 1965 – 1975 period. Altman's 1968 sample is from the period of 1946 – 1965. The error rate reported by Moyer for the Altman 1968 model is no less that 25%. Unfortunately the differences in the results are most difficult to reconcile. Re-estimation by Moyer of the parameters of Altman's 1968 model – using the 1965 to 1975 data – yielded an error rate of 10 percent. Moyers efforts must be judged considering the small sample size (27 bankrupt firms and 27 non-bankrupt firms). Ohlson adds 2 more predictors to his model to see if this improves the predictive power of his model. It does not. Other than the earlier mentioned timing issues the author is unable to account for the differences.

2.8 Cash Flow Based Models

Aziz, Emanuel and Lawson (1988) criticize the work of Beaver, Edmister, Altman and others who have built their bankruptcy prediction models around ratios. They claim that this way of work is based on ad hoc pragmatism rather than sound theoretical work. They classify it as a 'brute empiricism approach' using stepwise discriminant and / or regression analysis with selected variables that tend to be sample-data specific and of which the empirical findings do not permit generalization. Their view is that corporate bankruptcy is closely related to firm valuation and therefore a cash flow model should do better in effectively predicting corporate failure. The quality of signals given by cash flow based variables and historic-cost accounting measures of performance may be judged positively in this respect from the following example. From their sample, 7 companies in 1981 had price-earnings multiples significantly higher than the market but their cash flows were not encouraging. They all filed for bankruptcy in 1982. Thus, a theoretical and empirical rationale exists for formulating a hypothesis about corporate bankruptcy in terms of cash flow variables.

There are 2 components of earnings commonly used by managers to prevent losses: (I) cash flow from operations and (II) changes in working capital. Increases in earnings are associated with decreases or changes in working capital. For example, if we look at cash sales one may observe that when there is an increase in sales, it will consequently cause an increase in cash from operations. At the same time however, because the inventory decreases, so does the non-cash component of working capital. Cash flow from operations is not affected in the event that a firm makes additional sales on credit. It does increase receivables and decreases inventory for a net increase in working capital. As previously noted, changes in the quantity of working capital can be used to differentiate firms as they approach bankruptcy (Philosophov, 2006).

The CFB model (cash flow based model) that Aziz et al utilize in terms of results compares favorably with the ZETA® and Z-score models of Altman. Overall accuracy is approximately equal. Compared with the Z-score model the CFB model is substantially more likely to predict a bankruptcy up to 5 years prior to the actual event. When compared with the ZETA® model, the CFB model is more likely to provide an early warning 3 or more years before the event. However the ZETA® model is superior in the 2 years immediately preceding bankruptcy. The value of these conclusions is enhanced when considering that the coefficients of the ZETA® model are not publicly available. Besides that, practically the cost of misclassifying a potentially bankrupt firm is much higher than misclassifying a potentially non-bankrupt firm.

Less favorable comments on the use of cash flow based models come from Watson (1996). He claims that with respect to the use of cash flows to predict corporate bankruptcy, cash flow information does not contain any significant incremental information over other accounting information in order to discriminate between bankrupt and non-bankrupts enterprises. Viscione (1985) argues that cash flows from operations could be misleading because management's manipulation of the timing of cash flows, such as not paying bills in time or reducing inventory below desired levels. These insensible maneuvers increase the cash flow from operations reported in the income statement.

2.9 Predicting Failure and Payment Behavior

Wilson, Summers and Hope (1999) find that payment behavior data can add incrementally to the predictive ability of corporate failure models. The assessment of the ability and willingness of a firm to pay its creditors, and the likely timeliness of payments, are a major focus of both credit analysis from a trade credit perspective and corporate failure prediction.

Wilson, Summer and Hope's model is based on a linear combination of financial ratios reflecting liquidity, leverage, business activity and profitability along with variables derived from non-financial and payment behavior information such as industry type, company size and company age.

The authors perform their study on 7,034 companies in the United Kingdom, varying form sole proprietors to public limited companies across a wide range of industries. 3,133 companies of the sample failed during 1992, a year when the UK economy was in the depth of a recession and when it had the most business failures.

The authors look at the predictive power of the different types of data separately. Consideration has been given to the extent to which they are complementary. By combining variables they have constructed a model of best-fit. They find that the inclusion of non-financial data and a history of payment behavior in models can increase predictive ability over that achieved results with accounting data alone.

2.10 Revisiting Z-Score and ZETA® Models

Altman is concerned with an assessment of ratio analysis as an analytical technique since there have been many attacks on the relevance of ratio analysis by many esteemed members of the scholarly world. Therefore Altman (2000) extends his Z-Score and ZETA® models – which he developed in the late 1960's and the mid 1970's – to include applications to firms *not traded publicly* and to non-manufacturing entities.

Altman advocates to build upon previously cited studies based on univariate analysis (Beaver 1966) and combine several measures into a meaningful predictive model. By doing so the importance of ratio analysis as an analytical technique will be emphasized rather than downgraded. The questions are (I) which ratios are most important in detecting bankruptcy potential, (II) what weight should be allocated to those selected ratios, and (III) how should those weights be objectively established.

From a list of 22 potentially helpful ratios, 5 standard categories, are formed. Liquidity, profitability, leverage, solvency and activity. The ratios are chosen on the basis of their popularity in the literature and their relevance to the study. The final profile of variables is obtained by evaluating the significance and relative contribution of each dependent variable, the inter-correlation among the relevant variables and the observation of the predictive accuracy of the various profiles.

Altman acknowledges that his Z-Score model in essence is a publicly traded firm model. To apply the model to non-public companies calls for improvised changes – for example, to replace the market value of equity for the book value of equity – which are not scientifically valid. He advocates a complete re-estimation of the model rather than simply changing the 2 variables. Nevertheless, the results of the model with such changes appears to be only somewhat less reliable than the original. Due to lack of private firm data however, the model has not been tested extensively on secondary samples of distressed and non-distressed entities. Of all research this non-scientific alteration of an existing model for public companies comes closest to the study of small, non-public companies.

The discriminant function, *the model*, comprises X_1, working capital to total assets, X_2, retained earnings to total assets, X_3, earnings before interest and taxes to total assets, X_4, market value of equity to book value of total liabilities and X_5, sales to total assets. To adapt for non-manufacturing companies, sales to total assets (asset turnover) is taken out of the function. This is done in order to minimize the potential industry effect which is more likely to take place when such an industry sensitive variable as asset turnover is included.

The ZETA® credit risk model is a second generation model with several enhancements to the original Z-Score approach. There were several reasons for building this new version. One of them being that with some slight analytical adjustments, retailers, a particularly vulnerable group, can be analyzed on an equal basis with manufacturers. The most important aspect is that the most recent changes in financial reporting standards and accepted accounting practices are included. Adjustments are made in firms' assets, liabilities and equity. Drivers for these adjustments include capitalization of leases, reserves, minority interests, non-consolidated subsidiaries, goodwill and intangibles and capitalized research and development costs. Since the ZETA® model is a proprietary effort its parameters are not fully disclosed.

2.11 Multi-Period Classification

The models to forecast bankruptcy that have come by so far are single-period classification models, also referred to as static models utilizing multiple period bankruptcy data. Shumway (2001) claims that firms change through time. The bankruptcy probability that a static model produces however, does not vary with time. Therefore – according to Shumway – static models produce probabilities that are biased and inconsistent. Static models do not control for each period a firm is at risk. When sampling periods are long, it is important to control for the fact that some firms file for bankruptcy after many years of being at risk while other firms fail and file for bankruptcy at their first year of being at risk. Shumway proposes a so-called hazard model or duration model. Hazard models resolve the problems of static models by explicitly accounting for time. As opposed to static models, hazard models contain time-varying covariates, or explanatory variables that change with time. This is an advantage because it is important to consider a company's changing health when it deteriorates on its way to bankruptcy. Hazard models are a multi-period assessment, where multi-periodicity is understood to be the joint use of (many) past observations per each firm. Finally hazard models predict more efficiently because they use more data. The model includes each firm-year as a separate observation. Since for firms in a sample usually 5 years of financial data is available, 5 times more data is available to include in the analysis (a time series of annual observations). This results in better forecasts.

Shumway uses market-driven as well as accounting-based variables to identify bankruptcy risk. The market-driven variables include market capitalization, past stock returns and the idiosyncratic standard deviation of stock returns (that is the standard deviation of a structural behavior characteristic which is specific for a certain group, failed or non-failed). He concludes these are strongly related to bankruptcy probability. They are combined with the ratios of net income to total assets and total liabilities to total assets. He has tested his model with a set of bankruptcies over a period of 31 years and finds that half of the accounting-based ratios used in previous studies are poor predictors. Another variable of interest in Shumway's hazard model is the firm's age. Shumway uses the number of calendar years the firm has been trading on the NYSE (New York Stock Exchange) or AMEX (American Stock Exchange). He uses the trading age since a firm must meet a number of requirements to be listed by an exchange and firms are fairly homogeneous once listed. Shumway collected data from 2,497 firms, 28,664 firm years and 239 failures over a 30 year period of time. He does a meticulous comparison between previous studies by Altman (1968), Begley, Ming and Watts (1996) and Zmijewski (1984) and his own. He also interchanges variables and makes the comparison again and based on his comparison he concludes that his choice of variables is the best and his hazard model produces the best results. He finalizes with the results of his own model with market variables only and again testing his own model with market and accounting variables. The latter classifies 75 percent of bankrupt firms in the highest bankruptcy decile (upper 10%) and it only misclassifies 3,5 percent of bankrupt firms below the bankruptcy prediction median (the lower 50%). The model based solely on market-driven variables performs quite well too, classifying 69% of bankrupt firms in the highest probability decile and 95% of the bankrupt firms above the probability median.

2.12 Non-Financial Predictors of Bankruptcy

Bechetti and Sierra (2003) investigate *non-financial* explanatory variables of company failure. Their study looks at determinants in samples of 4,000 Italian manufacturing firms in the period 1989 until 1997. Important findings are that: (I) the degree of relative firm inefficiency, measured as the distance from the efficient frontier, has significant explanatory power in predicting bankruptcy; (II) qualitative indicators such as customers' concentration and the strength and proximity of competitors also have significant predictive power.

On the basis of the financial ratios that are successfully identified in other studies, 20 financial indices are chosen. These indices reflect 6 different aspects of firm structure and performance: liquidity, turnover, leverage, operating structure and efficiency, size, capitalization and profitability. They are calculated as 3-year, 2-year and 1-year averages. The variables that are effecting efficiency are: market share, strength and proximity of competitors, export status, subcontracting status, group membership, size, location (in a macro area of Italy) and C3-index (share of sales to the most important 3 customers). As an alternative to static ratios, a 3-year trend is calculated for each of the selected indicators following Edmister's (1972) methodology.

2.13 Firm-Specific and Macroeconomic Influences

Duffie et al (2007), like Shumway (2001), perform a multi period default prediction but incorporate the dynamics of firm-specific and macroeconomic covariates. They do so for American industrial firms, based on over 390,000 firm-months of data, spanning 1980 to 2004. The firm-specific covariates referred to are a firm's distance to default (which is the number of standard deviations of asset growth by which assets exceed a standardized measure of liabilities), a firm's trailing stock return, S&P 500 trailing stock returns and US interest rates.

Duffie et al apply a probabilistic (Bayesian-type) model for the prediction of corporate default with variables as proposed above. The data is obtained from quarterly and yearly Compustat files, Moody's Default Risk Service, Bloomberg and the CRSP database. The researchers find significant dependence of the state of the company on the current state of the economy and the current leverage of a company as captured by distance to default.

2.14 Concluding Comments

In this chapter I have revealed the development of bankruptcy prediction research through time. Over a period of some 40 years – 1966 to 2006 – 13 study's of just as much researchers and / or research groups, each with a different view on the matter and each considered to be an contribution to unraveling what's there to know, have come by. Every study tells us about the construction of a different model that – given the available data and thinking of that moment in time – conveys some kind of clarification on the subject. However, none of the models presented do so for the *prediction of corporate bankruptcy of private companies in The Netherlands*.

This paper continues doing exactly that. The next chapter exposes the theory that serves as the basis for developing this new model.

3 Theory

3.1 Introduction

Chapter 2 provides an overview of the development of academic research over time regarding the prediction of corporate bankruptcy in general. The most interesting studies, and the ones that have added to improved comprehension of the subject, are discussed. In the chapter to follow the theory that serves as the basis for this study will be explained.

3.2 Ground Rules

As a firm approaches bankruptcy one observes changes in the structure of its assets. For example, the proportion of current assets decreases and hence the relative value of fixed assets to total assets increases. Furthermore the decrease occurs mainly in the most liquid (quick) assets (cash and receivables), while inventories remain virtually unchanged. Also significant changes are revealed in the structure of the firm's liabilities. As bankruptcy approaches there is a noticeable increase in the current liabilities of the firm. Sometimes liabilities even exceed the firms total assets. The changes in the levels of current assets and liabilities of a firm suggest that their relation, or ratio, could be an indicator with forecasting ability in respect to bankruptcy.

To legitimize the use of ratios while predicting company failure, Beaver (1966) provides a framework for the selection of ratios. He describes the company as a reservoir of financial resources and the probability of company failure in terms of the expected flow of these resources. Other things being equal, one would expect that the probability of failure becomes more likely when:

• the reservoir is smaller. After all, a larger reservoir would be a better buffer against uncertainties;
• the inflow of resources from operations is smaller, in both the short-run and the long-run;
• the claim on its resources by creditors is larger;
• the outflow of resources that is required by the operation of the business is greater;
• the earnings and claims against the resources, represented by the outflows to maintain current operations and by obligations to creditors, are more highly variable. After all, the less variable inflows and outflows are, the more likely future events can be predicted, and / or
• the industry segment of a firm's business activities is expected to be more failure-prone

It appears that reliable functions are most likely formed with a set of independent predictors. Since ratios tend to be similar in their information content, great care has to be taken to select a group that is as diverse as possible. This leads to an important implication: maximum advantage is most likely obtained by selecting 1 ratio for each different characteristic of a borrowers business such as liquidity, profitability and solvency. Selecting more than 1 ratio is likely to result in additional computational and analytical effort without materially improving the result. Empirical research confirms the view that a small number of carefully selected ratios are as useful as many ratios in predicting failure.

3.3 Variable Selection

A complex set of data containing a large number of variables – in this case financial ratios – needs to be put in some kind of order to simplify interpretation. Removal of redundant variables may improve interpretability but it must be noted that as long as the correlation between 2 variables is less than 1, there is some variation in each variable which may be useful. This variation could potentially influence the outcome. It is impossible to reduce the number of variables without some loss of information. When one removes variables, one should make sure to retain as much relevant information as possible.

An important aspect of financial ratios is their statistical nature, specifically how they are distributed. Available information on this issue is somewhat limited. Most publications provide average financial ratios. Frequency distributions are never provided and measures of dispersion only rarely. The studies that do present information in this respect illustrate that financial ratios tend to be normally distributed. Normally distributed but somewhat positively skewed. The fact that they are positively skewed makes sense in a way that ratios have a certain lower limit but a more or less indefinite upper limit. The pattern of being normally distributed in general is important though since it means that financial ratios can be subjected to linear statistical techniques. In this study MDA specifically.

As to company size we may state that one of the basic functions of ratios is to take away the difference in accounting data between large and small companies. This adds to the presumption that stratification on company size is not necessary in financial ratio analyses. In regard to seasonal conditions and geographical location it is a common understanding that variations in ratios that are caused by these patterns are inherent to certain types of industry and hence will be captured by industry stratification of ratio data. There is no doubt that differences in accounting methods can cause financial ratio dispersion. It is however, not certain whether differences in accounting methods would significantly change ratio distributions within industries and whether adjustments of accounting data would make the ratios better predictors of dependent variables.

An interesting theory is that the predictive power of ratios seems to be cumulative. No single ratio predicts nearly as well as a small group do, and some ratios that are not significant predictors by themselves serve to improve discriminant ability when added to a function. However, when ratios are added without any consideration of independence to an analysis with ratios already included, the real predictive power of the analysis does not improve (Edmister 1972).

In summary, the essential statistical nature of financial ratios appears to be as follows: they are normally distributed, they are highly correlated with each other, they are highly correlated over time, and are subject to wide dispersion which can be reduced somewhat by industry stratification. Since there is no widely accepted theory as to whether which variables should be used precisely, it should be accepted that in general, and in bankruptcy prediction models specifically, the selection of the variables will be no less than an empirical exercise. This study makes use of variables which have been selected and used in similar studies based on their performance.

3.4 Bias and Validation

The objective of validation is to determine what part of the observed proportion of correctly classified observations is due to the true differences between groups. The possibility of bias due to intensive searching is inherent in any empirical study; sampling errors in the collection of firms and bias in selecting the ratios for the best possible profile. While a subset of variables or subset of firms is effective in the initial sample, there is no guarantee that it will be effective for the population in general. Importance of secondary sample testing can not be overemphasized. One type of secondary sample testing is to test a newly constructed model on a subset of the original sample, and then to classify the remainder of the total sample. This is the split sample approach or hold-out procedure recommended by Frank, Massey and Morrison (1965). A t-test may then be applied to test the significance of the results. A number of replications choosing different subsets from the original sample should indicate that there is a significant difference between bankrupt and non-bankrupt, meaning the model, in fact, possesses discriminating power on observations other than those from the initial subsample.

3.5 Concluding Comments

Chapter 3 provides the presentation of the theoretical framework for the prediction of corporate bankruptcy. This framework is used as a foundation in order to be able to apply the theory to small, private corporations in The Netherlands specifically. On this basis I continue to build by determining hypotheses that will elaborate on my expectations.

4 Hypotheses and Methodology

4.1 Introduction

The majority of studies available, are about public companies and focus on financial information that is available through pricing of securities on public exchanges. Studies that use ratios compiled out of internal accounting information only, generally use data of large public companies for the sake of availability of the data. This causes a misrepresentation of the smaller companies among which failure is a more common phenomenon. A relevant issue for Dutch firms and stakeholders is the question whether models that are known to work satisfactory on larger asset-size and public companies, do also hold on the Dutch, non-public market. As far as I am aware, no such study is available thus far, let alone on the Dutch market specifically. The remainder of this paper describes the method, the data collection and the findings of an empirical study about the prediction of bankruptcy of small Dutch, private companies that I conducted.

This chapter continues by studying 5 common financial ratios and by posing 3 hypotheses regarding the predictive capacity of the ratios in relation to discriminating between cases of bankruptcy and non-bankruptcy of small, private corporations in The Netherlands. A multiple discriminant analysis (MDA) is utilized to analyze the collected data and construct a function that enables to best discriminate between the 2 groups of companies all of which are registered at the Dutch Chamber of Commerce. The next paragraph will discuss the selected ratios and the hypotheses are presented. This is followed by a explanation of the methodology that is applied to the data.

4.2 Ratios

The ratios that are selected for this study are promoted by researchers and are found to be significant predictors of business failure in previous empirical research as per the literature review earlier in this paper. While the number of 5 ratios may seem somewhat limited, the set does contain the ratios that do say something about a complete range of vitality characteristics: liquidity, solvency, profitability and variability. The ratios that are included are *total debt to cash flow*, *net income to total equity* (which are both profitability measures), *total equity to total assets* (a solvency or leverage measure), *working capital to total assets* and *current assets to current liabilities* (which are both liquidity measures). No more ratios are included while their data are not available for this study. Also, there does not seem to be a need to add more ratios because the independence of the ratios within the above mentioned groups with alike ratios already included, is questionable. Previous research indicates that the real predictive power of the analysis does not improve, instead extra variables will add to additional computational and analytical effort without materially improving the end results (Robert O. Edmister, 1972).

The liquidity ratios tell us about the ability of the company to fulfill its short term obligations while the solvency or leverage ratios do so about this ability in the longer run. The profitability ratio indicates whether the business is able to improve on its liquidity and solvency situation. After all, if the company is profitable it will be able to fulfill its obligations in an increasing way and if not so, its situation will worsen and decrease its distance to default.

A large number of ratios per profitability, liquidity and solvability group is available. Beaver (1966) composed a list of no less than 30 of them and even this list is not exhaustive. Beaver uses 3 criteria to limit his selection to 30: (I) Popularity or frequent appearance in the literature, (II) performance in previous studies and (III) definition in terms of cash flow. The presence of any of these criteria was sufficient to include the ratio in his study. In a next step Beaver performed a univariate, dichotomous classification test. In other words, he tested the ability to classify between bankrupt and non-bankrupt of each variable individually. Table 2 reflects Beaver's top performing 5 ratios. Out of his list of 30, these are the ones with the lowest percentage misclassifications of bankrupt or non-bankrupt. Result-wise compared to all other study's discussed previously only Blum's classification results for one year prior to bankruptcy, are better. Considering that Beaver performed a univariate analyses using these ratios, a multivariate analysis using the same should result in more accurate findings. Hence these are the ratios that are selected for this study.

Table 2

Percentage of Firms Misclassified[(I)]: Dichotomous Classification Test

	Year(s) before Failure				
Ratio	**1**	**2**	**3**	**4**	**5**
Cash Flow / Total Debt (Profitability Measure)	0.10	0.18	0.21	0.24	0.22
	0.13	0.21	0.23	0.24	0.22
Net Income / Total Assets (Profitability Measure)	0.12	0.15	0.22	0.28	0.25
	0.13	0.20	0.23	0.29	0.28
Total Debt / Total Assets (Solvency Measure)	0.19	0.24	0.28	0.24	0.27
	0.19	0.25	0.34	0.27	0.28
Working Capital / Total Assets (Liquidity Measure)	0.20	0.30	0.33	0.35	0.35
	0.24	0.34	0.33	0.45	0.41
Current Assets / Current Liabilities (Liquidity Measure)	0.20	0.27	0.31	0.32	0.31
	0.20	0.32	0.36	0.38	0.45

[I] The top row represents the results of the test on a first subsample. The bottom row represents the results of a second sample.

Source: Beaver (1966)

Table 20 in the appendices represents Beaver's complete list of the 30 ratios including their classification ability results.

Furthermore a profile analysis is performed. Although a profile analysis has no predictive ability on its own, it may assist in interpreting the results obtained by means of the multiple discriminant analysis. It is able to demonstrate that there is a difference between failed and non-failed firms, but it can not explain how big that difference is while it concentrates on a single point of the ratio distribution, the mean. For further analysis we need additional information about the dispersion around the mean. This is provided by the MDA.

4.3 Hypotheses

The first and main hypothesis is that *ratios are useful to predict business failure of small, private firms in The Netherlands*. After all, a business is more likely to fail if, for instance, its current assets to current liabilities are 1 to 1 rather than 3 to 1. This hypothesis represents the use of ratios in its simplest form. The literature indicates that there is ample support for including an adjustment for industry type and company size. To honor the call to do so, the data for this study are obtained from one and the same industry segment: ‘Handel’ or ‘General Trade’. Chamber of Commerce’s SBI classification (Standaard Bedrijfs Indeling) 50 to 51, sector code 4 and 5, Central Bureau of Statistics (CBS) sector code 4. Table 5 in the data section reflects the subdivision of the Dutch industry by the Central Bureau of Statistics’ (CBS) classification criteria, enriched with figures from Failissementen.com. As to company size the data are stratified to include businesses of an asset size of up to € 4,400,000.00 only. As of the year 2006 (IFRS), companies with total assets of up to € 4.4 million, a turnover of up to € 8.8 million and up to 50 employees are classified as so-called small legal entities. These are the companies that are subject of this study. The ratios of the companies are compared to one another by means of the MDA analysis so as to – with respect to bankruptcy or non-bankruptcy – maximize the ‘between group’-variance while minimizing the ‘within group’-variance among them. This is repeated for a number of financial years in order to illustrate the predictive ability in time. Up to 5 years of data prior to failure are found optimal. Based upon validation tests, Blum (1974) concluded that his model had an accuracy of 94 percent when failure occurred within 1 year of the statement date. The accuracy declined to 80 percent for predictions 2 years prior to failure and to 70 percent 3 years prior to failure.

A second hypothesis is that *a 3-year-trend of a ratio is a predictor of failure of private firms in The Netherlands*. Earlier empirical studies by Blum (1969), Merwin (1942) and Smith (1935) conclude that trends of ratios (some more apparent than others) lead to business failure. After all, it appears to be a logical assumption that businesses that are ‘going the wrong direction’ should be viewed with greater caution than those whose trends are improving. A trend is defined as 3 consecutive years in which a ratio changes in the same direction. The ratios, together with their trends, are fed into the MDA to provide a prediction. Again, out of 5 years of ratios, 3 consecutive 3-year-trends may be obtained.

The third and last hypothesis is that *a 3-year-average of a ratio is a predictor of failure of private firms in The Netherlands*. Averaging smoothes the ratios. By doing so one moderates excessive figures and this results in a more representative figure than a single ratio from the most recent financial statement. The averages consequently are submitted to a multiple discriminant analysis for the same purpose as above. Out of 5 years of ratios, 3 consecutive 3-year-average ratios are obtained.

Expectations about the results of this study are high. Apart from the belief that the hypotheses will be true, the classification results are expected to be at least equal to Blum's result which is 94% of correct classifications, 1 year prior to bankruptcy. Justification for this proposition is that the ratios that are used are the ones that Beaver got better results with than any other study discussed previously, except for Blum's. Also considering the fact that Beaver performed a univariate analyses using his best scoring ratios, a multivariate analysis using the same should result in more accurate findings. Blum's precise pairing method and rigorous validation method that propagates making use of hold-out samples is used, Edmister's methodology of using trends is followed and Altman's theory on industry relative ratios reaching robust results is applied. The availability of a large, elaborate and accurate data set makes it possible to combine the strong points from some of the most highly regarded studies. Consequently this is expected to lead to high scoring results.

4.4 Methodology

The statistical problem in this study is one of classifying Dutch, private corporations as a member of 1 of 2 classes, bankrupt or non-bankrupt. This is done based upon a number of indicators, in this case the companies' financial ratios of a number of their financial years. As in several previous studies, multiple discriminant analysis (MDA) is used to construct a linear model which classifies individual cases based upon their historical financial ratios.

4.5 Multiple Discriminant Analysis

Multiple discriminant analysis (MDA) is a statistical technique used to classify an observation into 1 of several groups depending on the individual characteristics of the observations. MDA is used primarily to classify and / or make predictions in problems where the dependent (or to be explained) variable appears in qualitative form such as male or female, on or off, bankrupt or non-bankrupt. MDA is an alternative to logistic regression. It is preferred over logistic regression since it has more statistical power. MDA offers less chance of type II errors or accepting a false null hypothesis. Logistic regression is preferred when the data are not normal in distribution or when group sizes are very unequal. This study's data are normally distributed and the group sizes are equal. Hence the choice for MDA over logistic regression.

The first step is to establish group classifications. The number of groups can be 2 or more; in this study 2, bankrupt and non-bankrupt. Some researchers refer to discriminant analysis as multiple only when the number of groups exceeds 2. The most common view is that the multiple concept refers to the multivariate nature of the analysis.

After the groups are established, data are collected for the objects (the companies) in the groups. MDA in its most simple form attempts to derive a linear relation of these characteristics (the financial ratios) which best discriminates between the groups. If a firm has financial ratios which can be quantified for all of the companies in the analysis, the MDA determines a set of discriminant coefficients. When these coefficients are applied to the actual ratios there is a way to classify into one of the (mutually exclusive) groupings.

When utilizing a comprehensive list of financial ratios in assessing a firm's bankruptcy potential, there is reason to believe that some of the measurements will have a high degree of correlation or collinearity with each other. While this is not considered to be a serious problem in discriminant analysis it should motivate careful selection of the predictive variables (ratios). This will result in a model with a relatively small number of ratios that contain a great deal of information. Most important aspect is whether the information indicates significant and meaningful differences among groups.

The MDA technique has the advantage of being able to consider a range of variables common to the relevant firms, as well as the interaction between them. And, simultaneously rather than sequentially, examining individual characteristics. A univariate study only considers the measurements used for group determination one at a time. The discriminant function $Z = V_1X_1 + V_2X_2 + \ldots.. + V_nX_n$ transforms the individual variable values into a single discriminating score or Z-value to classify the firm bankrupt or non-bankrupt. The greater the firm's distress potential, the lower its discriminant score. $V_{1 \text{ to } n}$ are the discriminant coefficients calculated by the MDA and $X_{1 \text{ to } n}$ are the independent variables or actual values.

The essence of the procedure is to compare the profile of an individual firm with that of the 2 groupings. Once the values of the discriminant coefficients are estimated, it is possible to calculate discriminant scores for each firm in the samples, and based on this score to assign the firm to 1 of the 2 groups: bankrupt or non-bankrupt.

To illustrate the principle of MDA we take a look at 2 ratios (Total Debt to Total Assets and Current Assets to Current Liabilities), of 1 financial year, of 7 companies (A to G). Of those companies 3 have gone bankrupt in the year after the financial year we are assessing. See table 3.

Table 3
Visualization Bankrupt vs. Non-Bankrupt

Company	Total Debt / Total Assets	Current Assets / Current Liabilities	Classification
A	0.66	1.47	Non-Bankrupt
B	0.57	1.73	Non-Bankrupt
C	0.79	1.26	Non-Bankrupt
D	0.70	1.21	Non-Bankrupt
E	0.58	0.99	Bankrupt
F	0.48	1.38	Bankrupt
G	0.73	0.65	Bankrupt

When we plot the 2 ratios of both bankrupt and non-bankrupt companies is a diagram (see figure 1) it may be noted that in some way the data is linearly separable. Meaning we can draw a straight line to separate the 2 groups. Judging from this figure, the 'To Be Assessed Company' could belong just as easy to the Non-Bankrupt group as to the Bankrupt group.

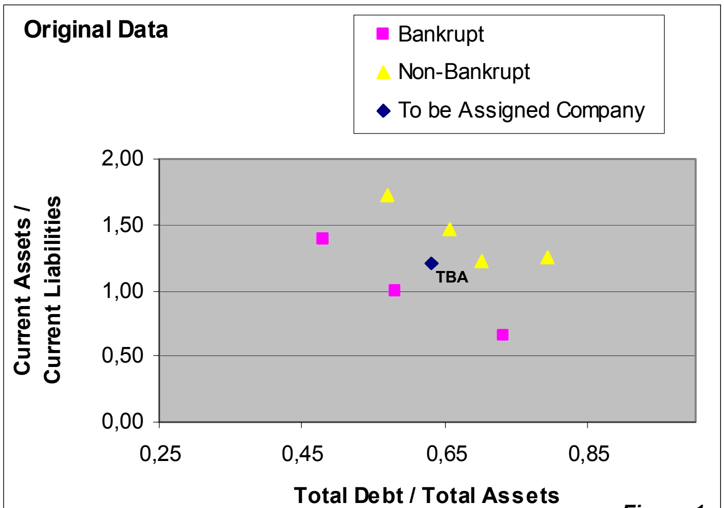

Figure 1

MDA is about the challenge to construct a function (a formula with a multiplier for each ratio and a constant) for each state (failed and non-failed) that recalculates the ratios' value and repositions it in the diagram so that along a straight line the distance between the groups is maximized and the distance within the groups is minimized. To do so the MDA calculates the functions for each case (company). See table 4 following.

Table 4
Visualization Bankrupt vs. Non-Bankrupt

Company	*f1*	*f2*	Classification
A	52.24	50.12	Non-Bankrupt
B	50.33	48.04	Non-Bankrupt
C	59.65	53.60	Non-Bankrupt
D	50.17	48.84	Non-Bankrupt
E	34.10	33.66	Bankrupt
F	31.71	32.99	Bankrupt
G	38.07	39.67	Bankrupt

Function 1 (*f1*) represents one state (non-bankrupt) and function 2 (*f2*) the other state (bankrupt). Each function is constructed to reach an outcome that lies as far apart as possible from the outcome of the other function. Consequently figure 2 visualizes neatly what happens. The imaginary company 'to be assessed' which is plotted in the original data's plot may be classified just as easy as bankrupt or as non-bankrupt. Whereas in the multiple discriminant plot (figure 2), after applying the functions, the distance to one of the groups along the line seems easier to establish. The company to be assessed will be classified as non-bankrupt in this case.

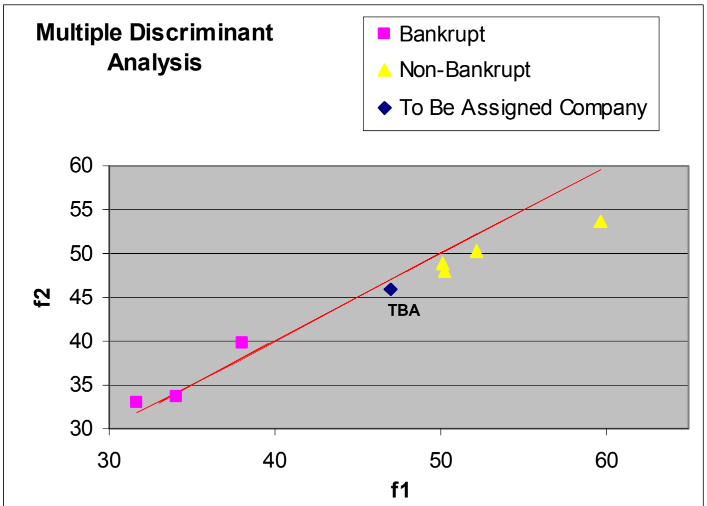

Figure 2

An MDA is performed for all cases (companies) in this study's dataset. It is done for each of their financial years by using the 5 designated ratios of that year. This results in 5 classifications (one for each year) per company. The same is done for the 3-year-average ratios which will result in 3 classifications (the average for years 1, 2 and 3, for the years 2, 3 and 4, and for the years 3, 4 and 5) per company. For the 3-year-trend analysis, dummy variables are introduced. If, for example, a ratio for the last 3 years has been 3 to 1, 2 to 1 and 1 to 1, it is classified as a trend. The ratio has moved in one direction over a 3 year period. No trend is considered for a ratio that has moved like 2 to 1, 3 to 1 and 1 to 1 over the past 3 years. Dummy variables for each trend are introduced into the equation. An upward trend dummy gets assigned a value of 1 if a trend is upward and a 0 for no trend. Also a downward trend dummy per ratio gets assigned a value of 1 if the trend seems to be downward and a 0 for no trend.

The multiple discriminant analysis models the value of the dependent categorical variable, bankrupt or non-bankrupt, and does so based on its relationship to a number of predictors, the ratios. Given a set of independent variables (the predictors, the ratios), the discriminant analysis attempts to find linear combinations of those variables that best separate the groups of cases. These combinations are called discriminant functions and have the form as displayed in the following equation:

$d_{ik} = b_{0k} + b_{1k}x_{i1} + ... + b_{pk}x_{ip}$

where d_{ik} is the value of the k^{th} discriminant function for the i^{th} case (company year)
b_{jk} is the value of the j^{th} coefficient of the k^{th} function
x_{ij} is the value of the i^{th} case of the j^{th} predictor (ratio)
p is the number of predictors (ratios)

The procedure automatically chooses a first function that will separate the groups as much as possible. It then chooses a second function that is correlated as little as possible with the first function and provides as much further separation as possible. The procedure continues adding functions in this way until reaching the maximum number of functions as determined by the number of predictors and categories in the dependent variable. The discriminant model has the following assumptions:

• The different ratios are not highly correlated with each other;
• the mean and variance of a given ratio are not correlated;
• the correlation between 2 ratios is constant across groups;
• the values of each ratio have a normal distribution.

The results will be checked for within-groups correlation (co-linearity) and the correlation of group means and variances. Also equality of co-variances across groups will be tested by using Box's M-test and Log determinants. Also, there are several tests that assess the contribution of each individual variable to the model, including tests of equality of group means. The tests of equality of group means measure each independent variable's potential before the discriminant model is created. Each test displays the results of a one-way ANOVA for the independent variable using the grouping variable as the factor. If the significance value is greater than 0.100, the variable probably does not contribute to the model. Wilks' lambda is another measure of a variable's potential. The smaller the outcomes of this test, the better the variable is at discriminating between groups. In addition to measures for checking the contribution of individual predictors to the discriminant model, the discriminant analysis procedure provides the eigenvalues (a vector multiplication factor) and Wilks' lambda tables for seeing how well the discriminant model as a whole fits the data. Wilks' lambda is a measure of how well each function separates cases into groups. It is equal to the proportion of the total variance in the discriminant scores which are not explained by differences among the groups. Smaller values of Wilks' lambda indicate greater discriminatory ability of the function. The eigenvalues table provides information about the relative usefulness of each discriminant function. When there are 2 groups, the canonical correlation is the most useful measure in the table, and it is equivalent to Pearson's correlation between the discriminant scores and the groups.

The MDA starts off with prior probabilities. A prior probability is an estimate of the likelihood that a case belongs to a particular group when no other information about it is available. Unless specified otherwise, it is assumed that a case is equally likely to be a bankrupt or non-bankrupt company (50/50). Prior probabilities are used along with the data to determine the classification functions. Adjusting the prior probabilities according to the group sizes can improve the overall classification rate. Should the initial outcome estimate that out of the sample 80% of the companies is non-bankrupt and 20% is bankrupt these values may be plugged into the model. Accordingly a priori, 80% of the cases are non-bankrupt, so the classification functions will now be weighted more heavily in favor of classifying cases as non-bankrupt. The overall classification rate will be higher for these classifications than for the ones based on equal priors. Unfortunately, this will come at the cost of misclassifying a greater percentage of bankruptcy. If one – in case of a bank officer considering a loan to a company – needs to be conservative in lending, then the goal is to identify bankruptcy, and one would be better off using equal priors. If one can be more aggressive in approving lending, then one may consider the use of unequal priors. Ergo: the use of unequal priors to take advantage of the fact that non-bankruptcy cases outnumber bankruptcy cases results in a higher overall classification rate but at the cost of missing bankruptcy.

4.6 Concluding Comments

What is supposed by this study and the methodology that will be adhered to testing the suppositions at correctness, are subject of the past chapter. Solid literature and theory research and ample consideration of leading researchers' views, sum up to the approach that will be followed in order to be able in the end to draw conclusions. Next the origin and nature of the data that is used to set the methodology in motion, will be discussed.

5 Data

5.1 Introduction

Following the hypotheses and methodology explained in the previous chapter, this chapter describes the data that forms the basis for the empirical part of this study and how the sample set is compiled. The data are obtained from Graydon Credit Management Services and from the Dutch Chamber of Commerce. Financial information on a total of 1,584 companies is gathered. Information on bankruptcies of corporations in The Netherlands is obtained from Faillissementen.com and miscellaneous supporting information is acquired from the Dutch Central Bureau of Statistics, the CBS.

5.2 The Dutch Sample

For almost every company in The Netherlands registration in the trade register is compulsory. The Dutch Chamber of Commerce manages the Dutch trade register. The register contains information on 1.6 million companies. By law companies have to submit their annual statements to the register. The Chamber provides several services. Besides the possibility to download a company's original statements, the Chamber offers statement extracts. An extract comprises balance sheet key figures as well as key ratios. These extracts are compiled and owned by Graydon Credit management Services. Graydon sources the data for this compilation from original statements that are recorded by the Chambers of Commerce.

This study is carried out for the Dutch market. Hence I have obtained information on Dutch companies. There is a call for the use of industry relative ratios. Analysis of ratios per industry. The main reason is to be able to control for industry differences such as changes in regulations, seasonal changes or different economic circumstances. Horrigan (1965) argues that a common characteristic of the statistical nature of financial ratios is the extent of the dispersion in ratio distribution within industries. Wide dispersion in financial ratio distributions may make discrimination between bankrupt and non-bankrupt firms difficult. A remedy to solve this problem is industry stratification. Since this study concerns bankruptcy prediction using financial ratios (only), this issue should be regarded as important with respect to the predictive accuracy. Altman et al (1984) used industry relative ratios in discriminant analysis in a study on 100 Australian firms and reached robust results. The trade segment General Trade is a segment with some 225,000 companies and 994,000 employees. In 2007 it suffered the highest number of bankruptcies, 1,340 in total. This segment offers the best chances for a reasonable size sample set. Annual reports' details of the years 2001 up to 2006 will be part of this study. This means that for companies being eligible to be part of the sample, they must be incorporated prior to the year 2001. This criterion further narrows down the 'bankrupt'-sample to 1,073 companies. Apart from stratification on the industry segment, further stratification is done on asset size. This is done for the same reason as stratification on industry segment classification, being that large differences in asset size may be of too much influence on the outcome. As per IFRS a distinction is made between so-called small, medium and large legal entities. Classification in one of the categories depends on, the net turnover (for small legal entities up to € 8.8 million), the number of employees (for small legal entities up to 50 employees) and the value of its total assets (for small legal entities up to € 4.4 million). Matching 2 out of 3 criteria leads to classification in the category. Small legal entities are obligated to submit a balance sheet only. Profit and loss statements are submitted on a voluntary basis. This means that a part of the data that the Chamber is able to offer is balance sheet data only. After all, the profitability ratios (total debt to cash flow and net income to total equity) contain information that has to come from the profit and loss statements. The data will also be trimmed meaning that the top and bottom 5% will be discarded to eliminate outliers. This is done for each and every variable. This further limits the final number of bankrupt companies available for this study to 792. A matching pair sample is drawn from the same industry segment, within the same asset size range of non-bankrupt companies. This results in a total sample of 1,584 companies. The completeness of data for these companies gets less every year further away from the year 2007, hence the fact that the sample size will decrease every year further away from the year 2007. The year 2002 has 403 failed and 403 not failed companies with a complete set of data.

Of all selected companies is known whether they have gone bankrupt in the year 2007 or whether they were still in business by the end of that year. Both cases, bankrupt and non-bankrupt, are represented for 50%. The statistical computer program SPSS is used to do all the selections, calculations and analyses. A random sample of approximately 70% of these companies is used to create the discriminant analysis model. The remaining companies are set aside to validate the model. Validation and cross-validation is done with the 2 remaining subsamples of 15% each. The model is used to classify the companies in these subsamples as having gone bankrupt or not. Reason is that classifications based upon the cases used to create the model tend to be too optimistic in the sense that their classification rate is inflated. The subsample-validation attempts to correct this. In cross-validation, each case is classified by the functions derived from all other cases than that case.

Another limitation is that companies have to have their annual figures submitted within 13 months of year end. This means that companies that go bankrupt in the year 2007 most likely will not have submitted their 2006 statements (nor will they ever), since 2006 statements do not have to be submitted sooner than by the end of January 2008. One more limitation is that not all registered companies actually do submit their annual reports (at all). Most apparent reasons for this is that they are not willing to make such information available for competing companies and that they are not willing to provide any such information because of the privacy of its owners. The companies that defy the obligation to submit their annual reports risk being fined substantially.

For an unknown reason the Dutch Chamber of Commerce's records are not quite up to date as far as the bankruptcy status of companies is concerned. The web based company www.failissementen.com is a Dutch bankruptcy database that updates its records on a daily basis. It holds data from the first of January 2003 with regard to bankruptcies, Chapter 11 and debt sanitation cases. 85,000 in total.

Failissementen.com uses court rulings to feed their database. Their data enables me to assign a bankruptcy status to the companies of which the annual reports' data are obtained from Graydon Credit Management Services with the highest possible precision. Faillissementen.com has registered 4,845 Dutch bankruptcies in the year 2007.

5.3 Sample Composition

Table 5 represents the composition of the population of this study. It comprises the entire Dutch trade, as per December 31st, 2007. The population is segmented by activity, according to the segment classification of the Central Bureau of Statistics (CBS). The table is complemented with the number of bankruptcies per segment by Faillissementen.com. The largest segment in 2007, in terms of bankruptcies and number of employees, is the General Trade segment. It has experienced 1,340 bankruptcies being close to 28% of the total and 994,000 employees being 26% of the total.

Table 5
Dutch Trade Segmentation by the Central Bureau of Statistics of The Netherlands

	Dutch Trade Segmentation		**2007**	
		Number of Bankruptcies [a]	**Number of Companies**	**Number of Employees**
1	Agriculture & Fisheries	50	31,402	100,080
2	Industry	391	61,047	724,861
3	Building & Construction	502	96,143	545,561
4	General Trade	1,340	225,022	993,798
5	Hotel & Catering Industry	300	45,865	172,594
6	Transportation & Communication	209	39,808	320,952
7	Financial Institutions	554	0 [b]	0 [b]
8	Industrial Services	762	252,014	774,866
9	Miscellaneous	218	65,939	135,406
	Not Classified	519		
Total		**4,845**	**817,240**	**3,768,118**

[a] By Failissementen.com.
[b] Not registered by the Dutch Central Bureau of Statistics (CBS).

5.4 Summary Statistics

Table 6 presents a summary of the statistics. The data are trimmed – the top and bottom 5% are excluded – to eliminate outliers that may incorrectly influence the outcome. The data are stratified by company size and industry segment. Only so-called small legal entities – total asset size < € 4.4 Million and number of employees < 50, from the general trade segment – have been included.

As noted previously, not all years, nor all ratios have an equal number of observations. Some ratios have a very limited number of observations. This is simply because not all the data are available. In particular profitability figures of companies that went bankrupt in 2007 fail. This may be explained by the fact that annual submission of profitability figures is not mandatory for small legal entities. A small number of observations also limits the possibility to eliminate outliers by trimming the data. Hence the fact that in some instances rather remarkable minimum and maximum figures are reported. Ahead of the conclusions it is worthy of mentioning that the notable minimum and maximum values reported, say something about the practical ability of the model constructed in this study. Apparently so it is very well possible to achieve reasonably high classification scoring results compared to – for instance – Blum who does a meticulous pairing of data. Obviously, precise pairing of data very much smoothes the range which makes it easier to make an outstanding value – i.e. that of a company on its way to bankruptcy – noticeable.

Table 6
Summary Statistics

	Min	Max	Mean	Median	Stdev	# Obs
CF 2002 Failed	0.06	0.24	0.15	0.15	0.06	8
CF 2003 Failed	-0.05	0.29	0.15	0.11	0.14	5
CF 2004 Failed	0.05	0.51	0.18	0.10	0.18	6
CF 2005 Failed	-0.32	2.34	0.24	0.08	0.77	10
CF 2006 Failed	-0.13	0.91	0.30	0.34	0.31	8
CF 2002 Not Failed	-0.15	0.66	0.16	0.13	0.15	1,519
CF 2003 Not Failed	-0.15	0.63	0.15	0.12	0.15	1,569
CF 2004 Not Failed	-0.18	0.63	0.14	0.12	0.16	1,282
CF 2005 Not Failed	-0.19	0.67	0.15	0.11	0.17	1,225
CF 2006 Not Failed	-0.26	0.73	0.16	0.12	0.18	940
NI / TE 2002 Failed	-65.95	250.00	39.41	18.55	77.30	17
NI / TE 2003 Failed	-181.47	85.17	-6.96	-0.03	65.29	19
NI / TE 2004 Failed	-305.00	83.95	-15.29	2.36	79.81	22
NI / TE 2005 Failed	-1,499.03	154.63	-174.17	-0.29	447.14	29
NI / TE 2006 Failed	-345.74	94.97	-27.63	-5.43	92.85	36
NI / TE 2002 Not Failed	-185.85	227.57	9.08	12.52	57.19	1,524
NI / TE 2003 Not Failed	-179.66	121.60	4.03	9.35	49.11	1,573
NI / TE 2004 Not Failed	-243.96	115.75	-1.54	7.06	56.24	1,284
NI / TE 2005 Not Failed	-191.41	113.99	0.84	8.31	52.83	1,226
NI / TE 2006 Not Failed	-154.70	121.96	6.24	10.99	50.02	939
SOLV 2002 Failed	-148.10	96.43	8.68	10.39	41.49	379
SOLV 2003 Failed	-179.60	89.20	2.04	7.05	50.00	474
SOLV 2004 Failed	-300.79	97.69	-6.26	5.03	64.73	548
SOLV 2005 Failed	-336.17	93.86	-16.10	1.00	69.86	619
SOLV 2006 Failed	-627.24	70.33	-50.15	-12.84	109.49	803
SOLV 2002 Not Failed	-48.03	58.67	17.46	19.01	20.96	1,524
SOLV 2003 Not Failed	-56.17	59.76	17.59	19.24	22.34	1,573
SOLV 2004 Not Failed	-90.88	63.99	13.83	15.01	27.61	1,284
SOLV 2005 Not Failed	-87.87	62.42	13.95	16.36	27.11	1,226
SOLV 2006 Not Failed	-151.00	65.61	12.30	16.67	34.51	939
WC / TA 2002 Failed	-99.00	82.96	4.89	6.10	38.12	363
WC / TA 2003 Failed	-125.70	85.73	-0.53	6.20	42.08	452
WC / TA 2004 Failed	-155.80	82.43	-5.45	1.56	47.64	521
WC / TA 2005 Failed	-290.81	71.97	-17.06	-4.27	55.44	592
WC / TA 2006 Failed	-411.26	67.07	-36.85	-13.63	79.21	792

WC / TA 2002 Not Failed	-37.97	59.54	14.57	14.72	21.94	1,524
WC / TA 2003 Not Failed	-41.64	59.50	14.79	15.54	21.88	1,573
WC / TA 2004 Not Failed	-54.17	62.48	12.70	13.46	24.28	1,284
WC / TA 2005 Not Failed	-54.33	63.26	13.96	14.38	24.23	1,226
WC / TA 2006 Not Failed	-63.73	67.45	11.84	13.26	26.45	939
CR 2002 Failed	0.16	8.34	1.48	1.09	1.29	361
CR 2003 Failed	0.15	9.45	1.40	1.09	1.30	448
CR 2004 Failed	0.12	11.21	1.36	1.02	1.41	516
CR 2005 Failed	0.10	6.04	1.13	0.95	0.87	585
CR 2006 Failed	0.09	4.68	0.96	0.85	0.68	782
CR 2002 Not Failed	0.42	4.64	1.49	1.29	0.77	1,521
CR 2003 Not Failed	0.44	4.78	1.49	1.31	0.79	1,573
CR 2004 Not Failed	0.32	5.03	1.50	1.27	0.87	1,283
CR 2005 Not Failed	0.33	5.36	1.50	1.28	0.86	1,222
CR 2006 Not Failed	0.23	6.73	1.56	1.27	1.10	936
TA 2002 Failed	18,200	2,670,260	647,865	430,561	634,718	378
TA 2003 Failed	18,002	2,376,571	545,975	334,041	551,248	472
TA 2004 Failed	17,725	2,204,958	478,649	279,738	507,949	548
TA 2005 Failed	18,151	2,076,602	463,865	279,084	470,441	618
TA 2006 Failed	18,000	2,082,773	460,650	282,042	470,609	803
TA 2002 Not Failed	137,477	4,259,414	2,323,309	2,607,066	1,378,548	1,524
TA 2003 Not Failed	136,190	4,261,008	2,373,142	2,709,617	1,360,618	1,573
TA 2004 Not Failed	83,466	4,249,109	2,002,534	1,956,217	1,438,613	1,284
TA 2005 Not Failed	89,848	4,254,528	1,921,786	1,646,680	1,434,610	1,226
TA 2006 Not Failed	70,924	4,270,556	1,788,080	1,371,199	1,446,537	939

5.5 Profile Analyses

The mean values of the used ratios may be computed for bankrupt and non-bankrupt firms in each year prior to bankruptcy. The assessment of the results in this way is called a profile analysis. A profile analysis is considered a way of simply depicting test scores. It should, however, not be regarded as a predictive test. Both Altman (1968) and Beaver (1966) argue that it is a convenient way of forming a general idea on the relationships between bankrupt and non-bankrupt firms. It can demonstrate a difference between bankrupt and non-bankrupt firms but it does not indicate the meaning of the difference. No meaningful statement can be made about the predictive ability of this type of analysis. The profile analysis also provides a convenient possibility to compare outcomes with outcomes from previous studies.

5.6 Concluding Comments

The obtained data reflects the financial situation of between 806 and 1,584 (the number varies per year prior to failure) small, privately owned corporations in The Netherlands. The data set is elaborate, accurate and complete and therefore will make it possible to answer the main question which is whether financial ratios are useful as predictors of small, private business failure. In the next chapter the findings will be presented.

6 Results

6.1 Introduction

In the previous chapters the literature and theory have been researched, the hypotheses posed and methodology decided upon. The data are obtained and the sample set is put in order. Next the model will be tested and in this chapter the results will be presented.

6.2 Comparison of Mean Values

The mean values of the 5 ratios of both the failed and non-failed companies are calculated of each financial year, up to 5 years before the year of failure, being 2007. The data of each ratio are presented in a diagram for which William Beaver (1966) coined the term *profile analysis*. The profile analysis is a convenient way of illustrating the relationships between failed and non-failed firms.

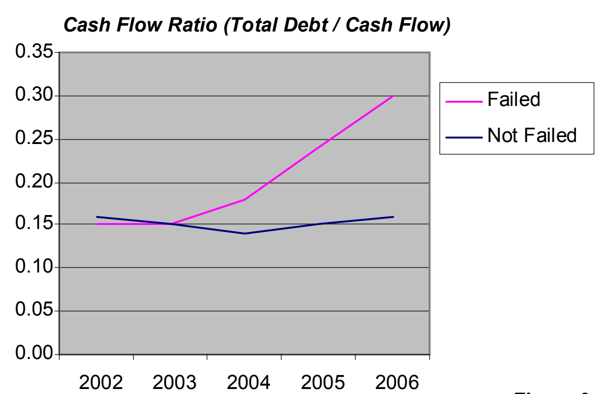

Figure 3

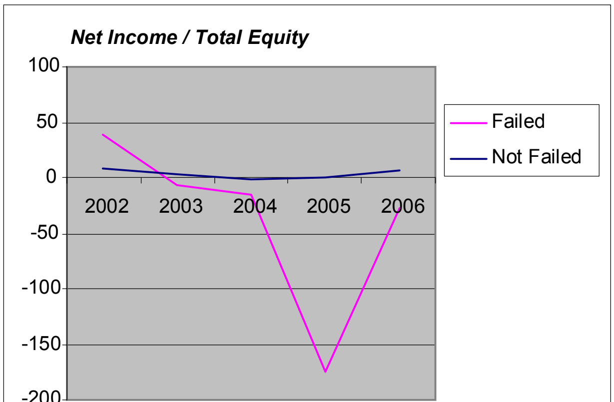

Figure 4

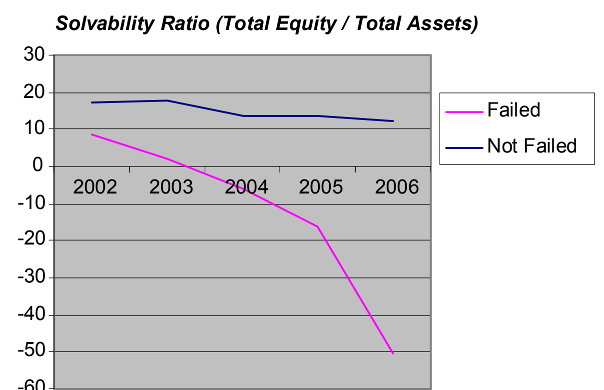

Figure 5

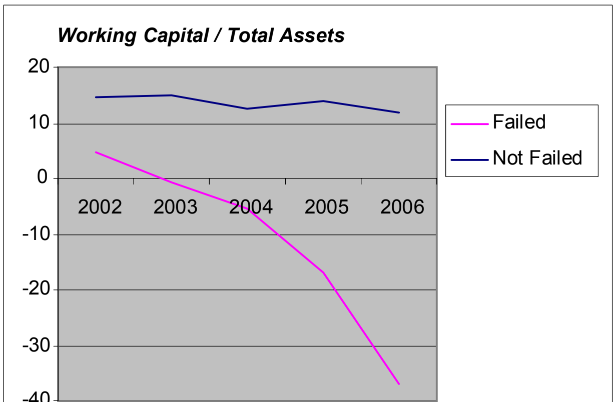

Figure 6

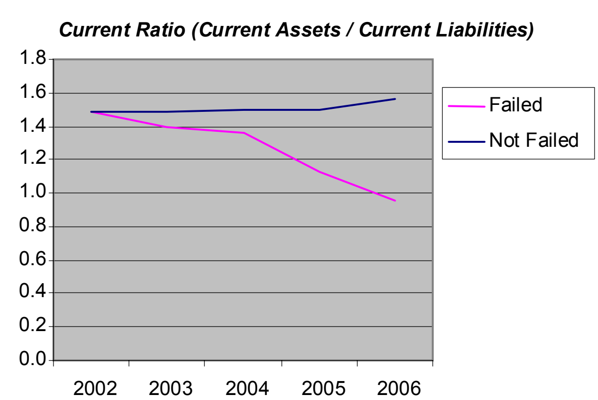

Figure 7

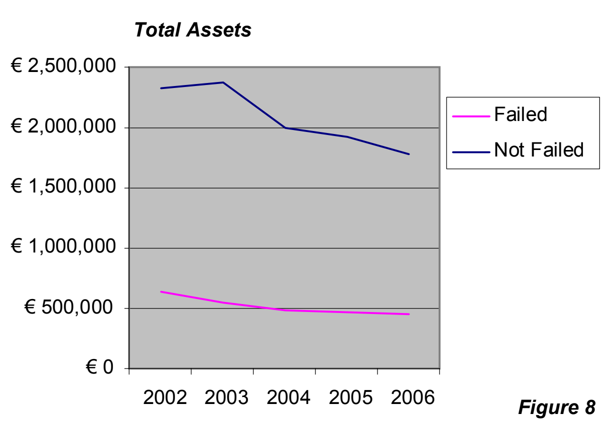

Figure 8

The figures clearly illustrate an increasing difference in the mean values of ratios between failed and non-failed firms when they move towards the year of failure. The differences become eminent, in some cases 5 and in some cases 4 years prior to the year of failure. What these differences indicate is that firms moving towards failure see their cash flows and their cash reserves go down. Apart from the fact that the failing companies have less capacity than their counterparts to fulfill their obligations, they also tend to acquire more debt. The trend lines of the healthy firms hardly slope and if they do deviate from being stable, the deviations are only small. Slopes in the trend lines of the failing firms on the other hand, are clearly observable.

The analysis also indicates that the mean of the total asset size of the failed and non-failed companies are quite different (see figure 8). The mean total asset sizes of the non-failing companies are clearly greater. The implications of different total asset sizes on the discriminant analyses to follow are hard to assess. Should the ratios and the asset sizes be correlated, the asset size difference may pose a problem. To assess correlation, correlation coefficients are calculated. The correlation coefficients (r) are shown in table 7 to follow. The square of the coefficient (r^2) indicates the proportion of the variance in a ratio that may be explained by the variation in asset size. An r^2 of close to 2% is the case with 2 of the 5 ratios. The others stay well below 1%. These results indicate that there is no evidence of a strong correlation between the ratios and the total asset size.

Table 7

Correlation of Total Assets with Ratios, Last Year Before Failure

Ratio	**Correlation Coefficient (r)**	**Proportion of Variance Explained (r^2)**
CF (Total Debt / Cash Flow)	-0.07	0.0049
NI / TE (Nett Income / Total Equity)	0.03	0.0009
SOLV (Total Equity / Total Assets)	0.14	0.0196
WC / TA (Working Capital / Total Assets)	0.13	0.0169
CR (Current Assets / Current Liabilities)	-0.03	0.0009

All profile analysis figures – apart from Cash Flow Ratio and Total Assets (figure 1 and 8) – show a downward trend as to be expected. Mean total assets show a slightly down going trend which suggests that companies show a negative growth over the period 2002 until 2006. For companies moving towards failure this is understandable as stated previously. Reserves are spent as the results are negative, decreasing total equity. The total assets drop is not prominent because this movement is attenuated by an increase in total debt as a result of negative results. Considering the movement of all other ratios of the healthy companies (they show no structural decrease) and an average general economic growth over the period under investigation of 1%[2], the drop in total assets most probably is due to the liquidation of assets. Figure 1 – cash flow ratio or total debt to cash flow – moves in the opposite direction. This is logical since for failing companies the cash flow decreases and the total debt increases resulting in an increasing ratio.

Although the profile analysis clearly illustrates differences between failed and non-failed firms, it does not offer an explanation on the size and the meaning of the differences. It merely pictures the mean values of the proposed indicators of failure. The size and shape of dispersion around the mean values is needed to be able to make sensible conjectures about the reasons for the differences.

6.3 Classification

I will continue to examine the data by means of the multiple discriminant analysis. In contrast to the profile analysis, MDA *is* a predictive test. The first tests comprise all 5 ratios of failed and non-failed companies. The results are very discouraging. In some cases – the year 2004 and 2005 – no failures at all are predicted correctly, in other words the tests return a type I error (false positive) of 100%. Close examination of the results reveals that 2 of the 5 ratios – the cash flow ratio and the net income to total equity ratio – do *not* contribute to the model, rather they frustrate the significance of the other ratios. This may be concluded from SPSS test output which provides several tables that assess the contribution of each variable to the model. Equality of group means – as per table 8 to follow – being one of them.

Table 8
Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
CF 2006	0.999	0.859	1	736	0.354
NI / TE 2006	1.000	0.109	1	736	0.741
SOLV 2006	0.999	0.453	1	736	0.501
WC / TA 2006	1.000	0.209	1	736	0.648
CR 2006	1.000	0.098	1	736	0.754

The tests of equality of group means measure each independent variable's potential before the model is created. Each test displays the results of a one way ANOVA for the independent variable. If the

[2] Central Bureau of Statistics (of The Netherlands), August 2008.

significance value is greater than 0.100, as per table 8, the variable does not contribute to the model. In the first test all values are considerably higher. Wilks' lambda per ratio (also table 8) is another measure of a variable's individual potential. Smaller values indicate that the variable is better at discriminating between groups. In the first test nearly all have the maximum value of 1 indicating that none are good predictors when all are used in one model.

Wilks' lambda is also a measure of how well each function separates cases into groups. It is equal to the proportion of the total variance in the discriminant scores which can not be explained by differences among the groups. Smaller values of Wilks' lambda indicate greater discriminatory ability of the function. Ideally the value should be lower than 0.100 to indicate a better result than chance. Table 9 indicates that for a function with all 5 variables it is too high and therefore not working.

Table 9
Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-Square	df	Sig.
1	0.994	4.545	5	0.474

Empirically, solvability (SOLV), working capital to total assets (WC / TA) and the current ratio (CR) appear to contribute the most to the model, do not correlate between each other heavily and show a good discriminative capacity. Significance of each, in each case, indicates better results than chance.

And so the test continues with 3 ratios instead of 5; 1 solvability and 2 liquidity type ratios remain. Table 13 to follow illustrates the results of every year's tests in timely order, starting with 1 year before failure and moving away to 5 years before failure. A decrease in overall percentage correctly classified is apparent while moving away from the year of failure. This seems acceptable since the distance to default gets bigger – i.e. the differences between failed and not failed get smaller – once one gets further away from the year of failure. After all the failing companies' ratios deteriorate coming closer towards the year of failure.

Examining the SPSS output tables of the test with 3 ratios of 1 year before failure and equal group sizes – these results are representative for the other years which will be left out to keep the paper orderly – results in the following: Wilks' lambda for the discriminant function returns significant. This is important as it indicates that the complete model judges far better than chance.

Table 10
Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-Square	df	Sig.
1	0.980	22.219	3	0.000

The Eigenvalue table (table 11) provides information about the relative efficiency of the discriminant function. When there are 2 groups, the canonical correlation is the most useful measure in the table. It is equivalent to Pearson's correlation between discriminant scores and groups. The lower this value is, the better is the models' ability to discriminate between failed and not failed.

Table 11
Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	0.020	100.0	100.0	0.131

Finally, the test of equality of group means indicates each independent variable's potential. Significance values of below 0.100 indicate that the variable contributes to the model. According to table 12 all variables in the 3-ratio composition of the model are significant.

Table 12
Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SOLV 2006	0.984	18.057	1	1111	0.000
WC / TA 2006	0.982	20.386	1	1111	0.000
CR 2006	0.991	1.773	1	1111	0.083

The results obtained by using the multiple discriminant analysis are presented in tables 13 and 14. Table 13 offers the results per year, for 5 consecutive years. The absolute number of failed and non-failed companies is presented as well as the percentages and the overall percentage classified correctly. Type I and type II error percentages are also stated.

To get a clearer picture of the predictive accuracy of the models, it is helpful to have a closer look at the type I and type II errors. A type I error occurs when a company has failed while it is predicted not to fail (false positive), and a type II error (false negative) is the opposite, a company did not fail while it is identified as going bankrupt. In case of the MDA analysis, 1 year prior to the year of bankruptcy, a type I error of 5.8% is reported. This means the model is right in 94 out of 100 cases of predicting that a company will not fail in the year 2007. The type II error of 64.4% of that same year is less precise. Out of 100 cases, 64 predictions of bankruptcy are false. If the bank manager needs to be conservative in lending, then the goal must be to identify defaulters. If the bank manager, on the other hand, seeks to be more aggressive in lending than the identification of non-defaulters may be used.

All classifications are based on equal chances of bankruptcy or non-bankruptcy. This means that the cut-off point is 0.5 on a scale of 0 to 1, equaling 50%. Each individual case may be judged additionally on its distance from the cut-off point. An individual case may get assigned a non-bankrupt value of 0.75

meaning that it has a chance of 75% to belong to the non-bankrupt group and 25% that it belongs to the bankrupt group. Based on the fact that there are much more companies that survive than companies that go bankrupt, the cut-off point may be adjusted accordingly. This means that the hit rate of bankruptcies will increase but at the cost of less accurate non-bankruptcy predictions. Either way the bank manager has possibilities to adjust the model to suit the requirements.

Table 13
Classification by Multiple Discriminant Analysis (Linear Model)

			Predicted		
			Not Failed	Failed	Percent Correct
2006 Ratios	Observed	Not Failed	746	46	94.2%
		Failed	518	274	34.6%
	Overall Percent Correct				64.4%
	Type I Error				5.8%
	Type II Error				65.4%
2005 Ratios	Observed	Not Failed	585	67	89.7%
		Failed	405	247	37.9%
	Overall Percent Correct				63.8%
	Type I Error				10.3%
	Type II Error				62.1%
2004 Ratios	Observed	Not Failed	508	68	88.2%
		Failed	383	193	33.5%
	Overall Percent Correct				60.9%
	Type I Error				11.8%
	Type II Error				66.5%
2003 Ratios	Observed	Not Failed	428	70	85.9%
		Failed	346	152	30.5%
	Overall Percent Correct				58.2%
	Type I Error				14.1%
	Type II Error				69.5%
2002 Ratios	Observed	Not Failed	290	113	72.0%
		Failed	241	162	40.2%
	Overall Percent Correct				56.1%
	Type I Error				28.0%
	Type II Error				59.8%

Table 14 contains the ratio trend and ratio average results. The data are presented in the same way as table 13. Trend 456 indicates the trend of each ratio for the years 2004, 2005 and 2006; trend 345 for the years 2003, 2004 and 2005; and trend 234 for the years 2002, 2003 and 2004. Dummy variables for the trend of each ratio form a new discriminant function. If the trend of a ratio over 3 years is upward, then the upward dummy gets assigned a value of 1. It gets a value of 0 if there is no trend. The downward trend dummy per ratio gets assigned a value of 1 if the trend seems to be downward and a 0 for no trend. The new discriminant function for a 3-year time slot thus comprises 6 variables; 1 upward and 1 downward trend dummy for each ratio. The MDA will consequently analyze all cases and produce a classification.

In case of the analysis of the averages the new discriminant function comprises 3 variables; a 3-year average for each ratio. The average classification results in the bottom part of the table are reported the same way as the trend classification results in the upper part of the table; the results of the averages for the years 2002, 2003 and 2004, for the years 2003, 2004 and 2005, and for the years 2004, 2005 and 2006.

Table 14
Classification by Multiple Discriminant Analysis (Linear Model)

			Predicted		
			Not Failed	Failed	Percent Correct
Trend 456	Observed	Not Failed	212	115	64.8%
		Failed	131	196	59.9%
	Overall Percent Correct				62.4%
	Type I Error				35.2%
	Type II Error				40.1%
Trend 345	Observed	Not Failed	237	90	72.5%
		Failed	152	175	53.5%
	Overall Percent Correct				63.0%
	Type I Error				27.5%
	Type II Error				46.5%
Trend 234	Observed	Not Failed	82	245	25.1%
		Failed	0	327	100.0%
	Overall Percent Correct				62.5%
	Type I Error				74.9%
	Type II Error				0.0%
Average 456	Observed	Not Failed	276	51	84.4%
		Failed	217	110	33.6%
	Overall Percent Correct				59.0%
	Type I Error				15.6%
	Type II Error				66.4%
Average 345	Observed	Not Failed	234	93	71.6%
		Failed	189	138	42.2%
	Overall Percent Correct				56.9%
	Type I Error				28.4%
	Type II Error				57.8%
Average 234	Observed	Not Failed	257	70	78.6%
		Failed	179	148	45.3%
	Overall Percent Correct				61.9%
	Type I Error				21.4%
	Type II Error				54.7%

The results, in general, are presented as '*percentage not-failed correctly predicted*', '*percentage failed correctly predicted*' and '*overall percentage correctly predicted*'. Having composed equal groups for all ratios prevents skewed overall percentage correctly predicted figures. For example, in many cases ratios for not failed companies are available in multiples of numbers for failed companies. A correctly predicted percentage of not failed of 80% of 1,000 not failed companies and 50% of 50 failed companies would result in an overall percentage correctly predicted of 79%. Whereas the same 80% of 50 not failed companies and 50% of 50 failed companies adds up to an overall percentage of 65%. To obtain equal group sizes, a random sample is drawn from the not failed companies group – which is much larger than the failed companies group – to equal the number of cases in the failed group of the same year.

The classification results per year indicate an increasing overall hit percentage when the number of years prior to the year of failure decreases. This is expected since a business is more likely to fail if, for instance, its current assets to current liabilities are 1 to 1 rather than 3 to 1. Based on these results the first hypothesis *(I) financial ratios are useful to predict business failure of small, private firms in The Netherlands*, is accepted.

The second hypothesis *(II) a 3-year-trend per ratio is useful to predict business failure of small, private firms in The Netherlands* is rejected. The results are instable; move up and down while a more pronounced difference, moving in one direction is expected. Trends typically move in a direction. A movement downward – for a ratio for which moving down means deterioration – does not necessarily mean movement towards failure within critical distance. Running a company more efficiently may cause downward trends too. In contrast to my results, Edmister (1972) reached good results with 3-year-average and 3-year-trend analyses but used a 12-variable model. Further along a more detailed comparison between studies and their results will be discussed.

The third and final hypothesis *(III) a 3-year-average of a ratio is useful to predict business failure of small, private firms in The Netherlands* is rejected also. As with the 3-year-average analysis, the 3-year average classification produces unstable results that move up and down where a consistent movement in one direction is expected. An improving hit rate is expected when coming closer to the year of bankruptcy. Averaging a ratio is expected to smooth the results. By doing so one moderates excessive figures and results in a more representative figure than a single ratio from the most recent financial statement. And so it does. However, apparently it smoothes out indicators needed to make the distinction between failed and not failed too much. Edmister (1972) – as put before – reached good results but he utilized far more ratios (12).

6.4 Alternative Tests

The data used for the described tests are not perfectly normally distributed around the mean. Therefore the normality of the data – which is a prerequisite for multiple discriminant analysis to obtain better results than logistic regression – may be argued. Logistic regression is a similar model used for prediction of the probability of occurrence of an event but by fitting data to a logistic curve.

Another alternative to MDA and LR is a so-called artificial neural network model. In practical terms neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Neural network models explore 'hidden' correlations between predictive variables which are then used as additional variables in – for instance – a non-linear bankruptcy prediction function. Neural networks come in various versions. One of them is the multilayer perceptron. This is a feed forward artificial neural network model (it adds – in this case – ratios as the model develops) that maps sets of input data onto a set of appropriate output. It is a modification of the standard linear perceptron in that it uses 3 or more layers of neurons (nodes) with non-linear activation functions, and is more powerful than the standard perceptron in that it can distinguish data that is not linearly separable such as is the case with MDA.

Logistic regression as well as neural network modeling produces output that is easier to interpret. This is the case because input usually involves fewer violations of assumptions – such as normality and within-group variances – that with MDA need to be interpreted each and every test. Both alternatives have been utilized to perform the same tests in order to be able make a comparison between the outcomes of different methods. The results are as per tables 15 to 18, presented in the same way as the MDA outcomes.

Table 15

Classification by Logistic Regression (Logistic Model)

			Predicted		
			Not Failed	Failed	Percent Correct
2006 Ratios	Observed	Not Failed	664	128	83.8%
		Failed	372	420	53.0%
	Overall Percent Correct				68.4%
	Type I Error				16.2%
	Type II Error				47.0%
2005 Ratios	Observed	Not Failed	441	211	67.6%
		Failed	251	401	61.5%
	Overall Percent Correct				64.6%
	Type I Error				32.4%
	Type II Error				38.5%
2004 Ratios	Observed	Not Failed	465	111	80.7%
		Failed	329	247	42.9%
	Overall Percent Correct				61.8%
	Type I Error				19.3%
	Type II Error				57.1%
2003 Ratios	Observed	Not Failed	345	153	69.3%
		Failed	289	209	42.0%
	Overall Percent Correct				55.6%
	Type I Error				30.7%
	Type II Error				58.0%
2002 Ratios	Observed	Not Failed	205	198	50.9%
		Failed	205	198	49.1%
	Overall Percent Correct				50.0%
	Type I Error				49.1%
	Type II Error				50.9%

Table 16
Classification by Logistic Regression (Logistic Model)

			Predicted Not Failed	Predicted Failed	Percent Correct
Trend 456	Observed	Not Failed	233	94	71.3%
		Failed	215	112	34.3%
	Overall Percent Correct				52.8%
	Type I Error				28.7%
	Type II Error				65.7%
Trend 345	Observed	Not Failed	258	69	78.9%
		Failed	219	108	33.0%
	Overall Percent Correct				56.0%
	Type I Error				21.1%
	Type II Error				67.0%
Trend 234	Observed	Not Failed	82	245	25.1%
		Failed	0	327	100.0%
	Overall Percent Correct				62.5%
	Type I Error				74.9%
	Type II Error				0.0%
Average 456	Observed	Not Failed	294	33	89.9%
		Failed	274	53	16.2%
	Overall Percent Correct				53.1%
	Type I Error				10.1%
	Type II Error				83.8%
Average 345	Observed	Not Failed	282	45	86.2%
		Failed	230	97	29.7%
	Overall Percent Correct				58.0%
	Type I Error				13.8%
	Type II Error				70.3%
Average 234	Observed	Not Failed	273	54	83.5%
		Failed	225	102	31.2%
	Overall Percent Correct				57.3%
	Type I Error				16.5%
	Type II Error				68.8%

Table 17
Classification by Neural Network (Logistic Model)

			Predicted		
			Not Failed	Failed	Percent Correct
2006 Ratios	Observed	Not Failed	570	222	72.0%
		Failed	201	591	74.6%
	Overall Percent Correct				73.3%
	Type I Error				28.0%
	Type II Error				25.4%
2005 Ratios	Observed	Not Failed	477	175	73.2%
		Failed	286	366	56.1%
	Overall Percent Correct				64.6%
	Type I Error				26.8%
	Type II Error				43.9%
2004 Ratios	Observed	Not Failed	469	107	81.4%
		Failed	296	280	48.6%
	Overall Percent Correct				65.0%
	Type I Error				18.6%
	Type II Error				51.4%
2003 Ratios	Observed	Not Failed	404	94	81.1%
		Failed	305	193	38.8%
	Overall Percent Correct				59.9%
	Type I Error				18.9%
	Type II Error				61.2%
2002 Ratios	Observed	Not Failed	185	218	45.9%
		Failed	123	280	69.5%
	Overall Percent Correct				57.7%
	Type I Error				54.1%
	Type II Error				30.5%

Table 18
Classification by Neural Network (Logistic Model)

			Predicted Not Failed	Predicted Failed	Percent Correct
Trend 456	Observed	Not Failed	245	82	74.9%
		Failed	79	248	75.8%
	Overall Percent Correct				75.4%
	Type I Error				25.1%
	Type II Error				24.2%
Trend 345	Observed	Not Failed	198	129	60.6%
		Failed	69	258	78.9%
	Overall Percent Correct				69.7%
	Type I Error				39.4%
	Type II Error				21.1%
Trend 234	Observed	Not Failed	268	59	82.0%
		Failed	109	218	66.7%
	Overall Percent Correct				74.3%
	Type I Error				18.0%
	Type II Error				33.3%
Average 456	Observed	Not Failed	265	62	81.0%
		Failed	201	126	38.5%
	Overall Percent Correct				59.8%
	Type I Error				19.0%
	Type II Error				61.5%
Average 345	Observed	Not Failed	236	91	72.2%
		Failed	138	189	57.8%
	Overall Percent Correct				65.0%
	Type I Error				27.8%
	Type II Error				42.2%
Average 234	Observed	Not Failed	228	99	69.7%
		Failed	104	223	68.2%
	Overall Percent Correct				69.0%
	Type I Error				30.3%
	Type II Error				31.8%

6.5 Comparison of Methods

Putting the results of the different methods of ratio analyses per year, together in one figure, results in figure 9. Multiple discriminant analysis and logistic regression produce comparable results. Logistic regression is slightly more pronounced. Neural Network scores slightly better than both others.

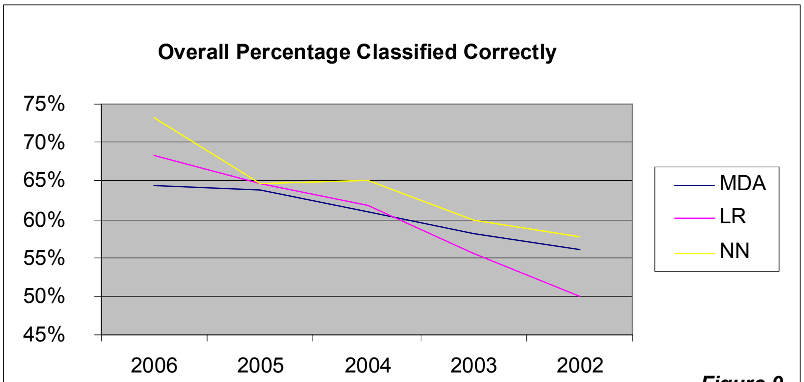

Figure 9

Both 3-year trend and 3-year average analysis produce unstable results as per figures 10 and 11. The results move up and down where a consistent movement in one direction is expected. This goes for all 3 classification methods.

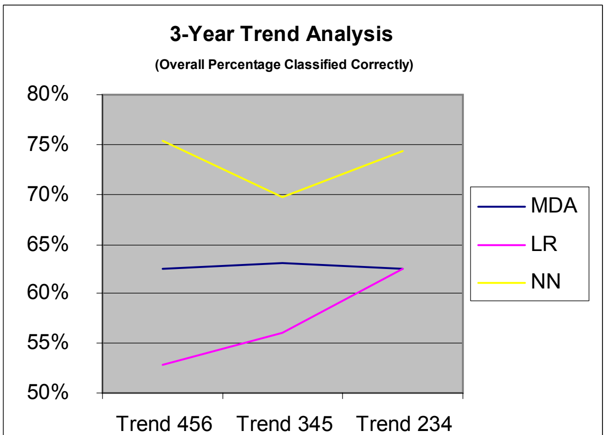

Figure 10

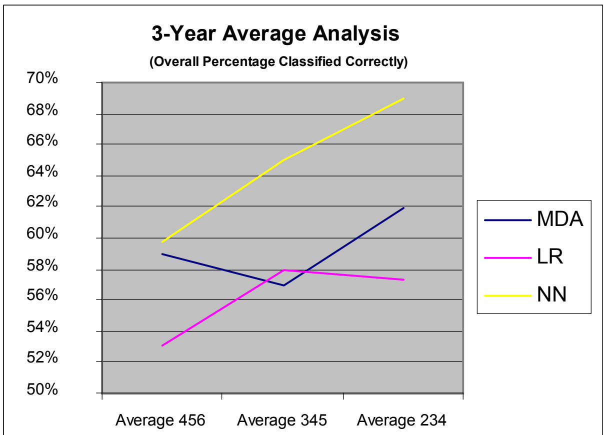

Figure 11

6.6 Comparison with Other Studies

The comparison of a number of studies, results in the figures presented in table 19. The table shows the scores of classification 1 year prior to bankruptcy and corresponding error II rates. The best score is on top. Most researchers use a linear discriminant method to classify a case as failed or not failed by using ratios or accounting-based variables as independents. Ohlson uses a logistic regression. I use both.

My results in the table are the results generated by the (logistic) neural network model. The outcomes of the studies are hard to compare other than simply looking at the percentages of the classification results. The sample sizes between studies do vary significantly. The number of variables used varies quit a bit too. All but one (Ohlson) use equal group sizes. All studies set out to examine whether ratios or accounting-based variables are useful in predicting failure. All conclude that ratios *are* useful as predictors of failure. Apart from that, they all do specify overall hit rates. An overall hit rate however, may be inflated compared to the actual default prediction. Since predicting failure is what all studies are all about, it seems appropriate to look at the percentage of type II errors. In that respect the differences are less prominent yet still apparent. Reasons for this may be various. Blum does quite a rigorous job in the pairing of sample sets. His sample sets are paired in terms of industry type, total asset size, sales, number of employees, fiscal year and total debt. Even though total asset size hardly correlates with the ratios used in this study, Blum’s results are quite extraordinary. Another point of interest is that the time slots in which the authors have conducted their research are quit different. This is known to account for part of the difference between the results as well. Blum’s research, for instance, has been duplicated by Campbell (1990) by using ratios from a time slot of 14 years later. His score of classification 1 year prior to bankruptcy is 84.2% or over 10% less good as the original research.

Table 19
Comparison of Studies

Author	Score	Type II Error	Sample Size	Model	Method
Blum (1974)	94%	7%	44	19-Variable Model	MDA
Edmister (1972)	93%	20%	230	12-Variable Model	MDA
Beaver (1966)	87%	21%	79	Univariate Model	DA
Altman (1968)	79%	24%	66	7-Variable Model	MDA
Ohlson (1980)	76%	27%	2,163	9-Variable Model	LR
Slotemaker (2008)	73%	25%	1,582	3-Variable Model	NN

The overall percentages classified correctly do lie quite a bit apart. The type II error range however, is not spread as much. In fact 5 of the 6 outcomes are between 20% and 27%.

The results do not mean that predicting corporate failure among small, private businesses in The Netherlands is more difficult than doing so for public companies. Provided that the data is available. The fact that the results of this study are slightly less pronounced compared to other studies – yet very much usable – is mainly explained by not utilizing the precise matching of cases. The precise matching of data results in a narrow data bandwidth which makes it easier to notice an outstanding value – i.e. that of a company that is on its way to bankruptcy. Exact matching of data however, is a very time-consuming exercise. Every time the bank manager has to decide whether to grant a loan, as many companies as possible that match the applicant’s data will have to be selected to do the analysis. Not having to do so and yet having considerable discriminating power makes the model constructed in this study much more versatile to apply and therefore more valuable.

6.7 Concluding Comments

The results of this study are consistent with, but not as pronounced as results in other papers that have studied the same phenomena. This is the case even though in this study it was set out from the beginning to achieve exceptional scoring results by stratifying the data for company size and industry type, the use of hold-out samples and subsample validation. Important reasons for this are most likely too prominent differences between group cases – better pairing results in better scores – and timing. Duplication of studies using data from later time slots returned quite different (less good) results. In one case disproportionate group sizes lead to an inflated overall percentage classified correctly (Ohlson, 1980). The main purpose of the study lying before you, however, is to establish whether ratios are useful as predictors of small, private companies in The Netherlands. This goal has been achieved.

To summarize; ratios *are* useful as predictors of failure when we intend to judge relatively small, private businesses in The Netherlands. From this we may conclude that a small, private, Dutch enterprise is more likely to go bankrupt if it is: unprofitable, small, highly leveraged, has liquidity problems, has a negative equity situation and or has less financial flexibility to invest in itself.

Even though the main goal of this study has been achieved, the quest for higher classification results, when using ratios as predictors of corporate failure, remains. The next and final chapter will discuss issues, methods and ways of handling data that may be eligible for improvement and consequently this study will be concluded.

7 Conclusions and Recommendations

7.1 Introduction

After reviewing the results of this study, the moment has come to conclude. Questions arise: Has the study answered the questions that have been set out in the beginning? Has it delivered new insights, new views? What do the results of this study mean for research on credit risk in general. Also what supplementary research must or may be done to improve or enlarge the overall knowledge of this field of interest?

7.2 Conclusions

The main question to be answered by this paper is whether *a financial ratio is useful to predict business failure of small, private firms in The Netherlands.* Additionally the hypotheses *a 3-year trend of financial ratios* and *a 3-year average of financial ratios, are useful to predict business failure of small, private firms in The Netherlands*, are posed.

A humongous set of 269,000 records – highly exceptionally, yet very kindly arranged by Graydon Credit Management Services – has been ploughed through and put in order to extract some 1,600 cases, consisting of equal numbers of failed and non-failed companies, to make the effort.

The answer to the main question is positive. Even though the trend and average analyses have not contributed to answering the main question, it may be stated that financial ratios *are* to be considered predictors of business failure. And specifically so in the case of relatively small, private corporations in The Netherlands. It is all about this final line. No research has been conducted on small, private businesses in The Netherlands before. The availability of the data has been a good opportunity do this research.

Even though the scoring results are not as high as hoped for, the final conclusion is that overall this thesis – at least through the eyes of the author – leaves a solid and satisfactory impression.

7.3 Recommendations

Practically, the bank manager will be interested in a model that has the highest discriminating power achievable and yet is as versatile as possible. This means that the model should be useable across industries, with different types of companies and that it may be applied without time restraints. To achieve such a model, the following topics should be subject of further research:

• Better pairing of samples does have a positive influence on the classification results. This is established by Beaver (1966) who repeated a part of his study with sample sets that were paired in terms of total asset size, sales, number of employees and total debt. Some of his ratios predicted up to 33% better. Blum also reached high scores using precise pairing. So for further research into the precise influence of pairing of cases is of interest;

• Timing is of the essence when we consider the duplication of Blum's research which indicates that some 14 years later the exact same study returns significantly different results. Apparently the ratios of the companies selected, are sensitive to differences in economic situations. It is eminent to understand what economic situation influences what variables and how;

• Since MDA is known to offer better results compared to logistic regression provided that the data are normally distributed around the mean, a challenge remains to find a way to linearize the data. How can we convert data to fit into a small bandwidth so to be able to more easily identify an outstanding value or a company that is on its way to bankruptcy;

• Cross-sectional models in general are criticized for attempting to model a dynamic process (such as the path to bankruptcy) using an essentially static framework. For instance, the variables in a discriminant or logit model do not vary (within one period) and thus assume a steady state for the bankruptcy process as opposed to a multi-stage process. This means that cross-sectional models give no indication of time-to-failure whereas going bankrupt usually does not happen from one moment to the other.

7.4 Concluding Comments

Practically, a credit issuing institute's lending decision may be viewed as a dichotomous decision to accept or reject a credit application. The objective of a ratio analysis is to classify a firm as acceptable or not. However, this is not all there is to it, of course. One may take a look at the track record or reputation of the company, the same of the management of the company, chances that management will change in due course, and there is a decision to be made about the size of the loan and the interest rate to apply. The latter two may be adjusted to suit the risk profile proposed by the classification test that has been discussed in so much detail in this paper. I feel that the proposed method will be additionally helpful in resolving credit risk issues in case of small, private corporations in The Netherlands and with that is a valuable contribution to the literature on financial distress.

A bank is a place that will lend you money if you can prove that you don't need it.
– Bob Hope (1903 – 2003) –

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10 Appendices

Table 20 represents Beaver's complete list of the 30 ratios including their classification ability results.

Table 20

Percentage of Firms Misclassified: Dichotomous Classification Test(I)

Ratio	Year(s) before Failure				
	1	2	3	4	5
Cash Flow / Sales	0.11	0.19	0.24	0.33	0.31
	0.14	0.20	0.29	0.37	0.44
Cash Flow / Total Assets	0.10	0.17	0.20	0.26	0.25
	0.10	0.20	0.24	0.28	0.28
Cash Flow / Net Worth	0.11	0.16	0.24	0.31	0.32
	0.13	0.21	0.28	0.38	0.37
Cash Flow / Total Debt	0.10	0.18	0.21	0.24	0.22
	0.13	0.21	0.23	0.24	0.22
Net Income / Sales	0.09	0.16	0.24	0.28	0.27
	0.13	0.22	0.28	0.35	0.31
Net Income / Total Assets	0.12	0.15	0.22	0.28	0.25
	0.13	0.21	0.23	0.29	0.28
Net Income / Net Worth	0.10	0.18	0.26	0.31	0.28
	0.13	0.26	0.26	0.34	0.40
Net Income / Total Debt	0.08	0.16	0.20	0.26	0.26
	0.15	0.20	0.22	0.26	0.32
Current Liabilities / Total Assets	0.27	0.28	0.34	0.33	0.30
	0.30	0.41	0.36	0.40	0.46
Long-Term Liabilities / Total Assets	0.32	0.40	0.40	0.38	0.41
	0.36	0.45	0.42	0.47	0.51
Current + Long-Term Liabilities / Total Assets	0.19	0.26	0.29	0.31	0.33
	0.23	0.30	0.36	0.39	0.38
Current + Long-Term + Preferred / Total Assets	0.19	0.24	0.28	0.24	0.27
	0.19	0.25	0.34	0.27	0.28
Cash / Total Assets	0.25	0.28	0.30	0.34	0.31
	0.28	0.29	0.30	0.36	0.38
Quick Assets / Total Assets	0.34	0.36	0.36	0.37	0.34
	0.38	0.42	0.36	0.48	0.40
Current Assets / Total Assets	0.37	0.44	0.43	0.43	0.38
	0.38	0.48	0.48	0.47	0.49
Working Capital / Total Assets	0.20	0.30	0.33	0.35	0.35
	0.24	0.34	0.33	0.45	0.41
Cash / Current Liabilities	0.22	0.24	0.28	0.34	0.29
	0.22	0.28	0.36	0.38	0.38
Quick Assets / Current Liabilities	0.24	0.30	0.28	0.34	0.29
	0.24	0.32	0.40	0.34	0.37
Current Assets / Current Liabilities	0.20	0.27	0.31	0.32	0.31
	0.20	0.32	0.36	0.38	0.45
Cash / Sales	0.30	0.24	0.34	0.39	0.41
	0.34	0.24	0.36	0.43	0.45
Receivables / Sales	0.40	0.39	0.38	0.37	0.38
	0.46	0.45	0.46	0.43	0.42
Inventory / Sales	0.40	0.50	0.47	0.42	0.42
	0.47	0.50	0.54	0.48	0.53
Quick Assets / Sales	0.40	0.42	0.40	0.48	0.42
	0.46	0.47	0.45	0.52	0.44
Current Assets / Sales	0.42	0.40	0.42	0.47	0.47
	0.44	0.51	0.48	0.49	0.51

Working Capital / Sales	0.23	0.27	0.35	0.40	0.37
	0.26	0.33	0.42	0.46	0.40
Net Worth / Sales	0.28	0.33	0.38	0.38	0.38
	0.32	0.36	0.44	0.42	0.40
Total Assets / Sales	0.34	0.40	0.34	0.38	0.39
	0.37	0.42	0.38	0.42	0.44
Cash Interval	0.26	0.27	0.32	0.42	0.38
	0.33	0.27	0.35	0.42	0.43
Defensive Interval	0.34	0.40	0.41	0.47	0.43
	0.39	0.41	0.46	0.48	0.51
No-Credit Interval	0.23	0.38	0.43	0.38	0.37
	0.23	0.31	0.30	0.35	0.30

[I] The top row represents the results of the test on a first subsample. The bottom row represents the results of a second sample.

Source: Beaver (1966)

11 Glossary

A Priori In statistics, a priori knowledge refers to prior knowledge about a population, rather than that estimated by recent observation. It may be based upon intuition and / or hypothesis rather than on experiment.

Barrier Option An exotic option that either comes to life (is knocked-in) or is extinguished (knocked-out) under conditions stipulated in the options contract. The conditions are usually defined in terms of a price level (barrier, knock-out or knock-in price) that may be reached at any time during the lifetime of the option. There are 4 major types of barrier options: up-and-out, up-and-in, down-and-out and down-and-in. The extinguishing or activating features of these options mean they are usually cheaper than ordinary options, making them attractive to purchasers looking to avoid high premium.

Bayesian Approach Bayes' Theorem relates the conditional and marginal probabilities of 2 random events. It is often used to compute posterior probabilities given observations. For example, a patient may be observed to have certain symptoms. Bayes' theorem can be used to compute the probability that a proposed diagnosis is correct, given that observation.

Canonical Correlation In statistics, canonical correlation analysis, introduced by Harold Hotelling, is a way of making sense of cross-covariance matrices.

Covariate (Covariable) An independent variable, or predictor, in a regression equation. Also, a secondary variable that can affect the relationship between the dependent variable and independent variables of primary interest in a regression equation.

Credit Default Swap (CDS) The buyer of a credit default swap is insured against third party credit losses. If the third party defaults, the company will have to purchase the defaulted asset from the insured party and also pay the insured the remaining interest on the debt and the principal. The company earns fee income on these products.

Defensive Interval A conservative measure of a company's ability to satisfy its debts, found by calculating how long it can operate on current liquid assets, without additional revenues. The ratio equals defensive assets (cash, marketable securities, and receivables) divided by projected daily operational expenditures less noncash charges.

Distance-to-Default The number of standard deviations of assets (or assets growth) by which assets exceed a standardized measure of liabilities.

Dummy Variable Also known as indicator or bound variable. Is one that takes the values 0 or 1 to indicate the absence or presence of some categorical effect that may be expected to shift the outcome. For example, in econometric time series analysis, dummy variables may be used to indicate the occurrence of wars, or major strikes.

Efficient Market Hypothesis (EMH) Asserts that financial markets are 'informationally efficient', or that prices on traded assets, e.g., stocks, bonds, or property, already reflect all known information. The efficient market hypothesis states that it is impossible to consistently outperform the market by using any information that the market already knows, except through luck. Information or news in the EMH is defined as anything that may affect prices that is unknowable in the present and thus appears randomly in the future. Ph.D. dissertation by Professor Eugene Fama (1960).

Eigenvalue In mathematics, a vector may be thought of as an arrow. It has a length, called its *magnitude*, and it points in some particular direction. A linear transformation may be considered to operate on a vector to change it, usually changing both its magnitude and its direction. An eigenvector of a given linear transformation is a non-zero vector which is multiplied by a constant called the Eigenvalue as a result of that transformation. The direction of the eigenvector is either unchanged by that transformation (for positive eigenvalues) or reversed (for negative eigenvalues).

Ex-Ante Before the fact, anterior, in foresight.

Ex-Post After the fact, posterior, in hindsight.

Heuristics Are rules of thumb, educated guesses, intuitive judgments or simply common sense.

Hold-Out Sample A hold-out sample is a subset of the data available to a data analysis which is used as the test set. A hold-out sample is used to assess the likely future performance of a prediction or classification model based on its performance with the subset or validation set.

Idiosyncratic Is defined as a structural or behavioral characteristic peculiar to an individual or group.

Linear Discriminant Analysis (LDA) A method that is used to find the linear combination of features which best separates (discriminates) 2 or more classes of objects or events (bankrupt and non-bankrupt).

Linear Probability Model Econometric model in which the dependent variable is a probability between 0 and 1. These are easier to estimate than probit or logit models but usually have the problem that some predictions will not be in the range of 0 to 1.

Linear Programming Model A technique for finding the maximum value of some equation (such as maximum profit or lowest cost), subject to stated linear constraints.

Logit Model (Logistic Regression or Model) A logistic [0, 1] regression analysis that uses more than one variable (multivariate). Chance of death by overweight, age, smoking, sex, et cetera.

Markov Chain Given the present, the future is conditionally independent of the past. Nothing that has happened in the past can influence or determine the outcome in the future, the future is all possibilities. A basic example is a coin toss. Markov determines chances of state changes using stochastic variables.

Multivariate Statistic (Multivariate Analysis) A statistical analysis in which more than one variable are analyzed at the same time.

Net Worth Amount by which assets exceed liabilities. For a corporation, net worth is also known as stockholders' equity or net assets. Measure of liquidity.

Option Pricing Theory (Black & Scholes 1973) Model that determines the price of an option by 5 variables: Stock Price, Risk Free Return Rate, Variance of Stock Return, Time to Maturity en Exercise Price of the Option.

Probit (Probability Unit) Model A probit model is an econometric model in which the dependent variable can be only 1 or 0.

Proxy Legal or valid replacement.

SBA Small Business Administration (USA).

SME Small and Medium Size Enterprises (USA).

Stochastic (Random) Variables Variables that have been assigned values drawn at random from a population.

Systematic Risk The risk inherent to the entire market or entire market segment. Also known as 'un-diversifiable risk' or 'market risk'.

Type I Error (False Positive) The error of rejecting a hypothesis that should have been accepted.

Type II Error (False Negative) The error of accepting a hypothesis that should have been rejected.

Univariate Analysis Analysis of a single indicator (the dependent or to be explained variable); univariate analysis is generally the first step in the analysis of a body of data; it is undertaken to describe each variable in terms of measures of central tendency (mean, median or mode) and variability (range, variance or standard deviation). ANOVA, t-test.

Unsystematic Risk Company or industry specific risk that is inherent in each investment. The amount of unsystematic risk can be reduced through appropriate diversification. That is, to divide investment funds among a variety of securities with different risk, reward, and correlation statistics so as to minimize investment risk.

Working Capital Current (short term) assets minus current (short term) liabilities (also net current assets of current capital). Measure of liquidity.