A FINANCIAL EARLY WARNING SYSTEM FOR FINANCIAL INTERMEDIARY INSTITUTIONS BY NEURAL NETWORKS

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A FINANCIAL EARLY WARNING SYSTEM FOR FINANCIAL INTERMEDIARY INSTITUTIONS BY NEURAL NETWORKS

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Thesis Abstract

M.K. Tahir Demircioglu, “A Financial Early Warning System for Financial Intermediary Institutions by Neural Networks”

The 2008 economic crises revealed that the existing financial system requires better monitoring and more effective regulations of the financial institutions. Straightforward implementation of tighter regulations will increase the costs of the financial system which will eventually hurt economic development. In order to minimize the effects of tighter regulations on the costs, regulators shall also consider taking advantage of new methods which are more complicated than existing ones. This dissertation proposes a financial early warning system for broker dealers in Turkey. Discriminant Analysis and Neural Networks are used comparatively and cooperatively to develop the model tailored for broker dealers. An extensive database is formed by Capital Adequacy Reports that were collected by Capital Markets Board for the period between 1999 and 2009. Access to this database contributed to this study in many ways through its tailored structure truly reflecting the financial standings of this industry. Popular independent variables in the literature are used and new ones are also proposed in order to take advantage of the details in the extensive database. Discriminant Analysis is used to elect the important independent variables that formed the backbone of the model, although most of the important a priori assumptions were violated. Neural Networks picked up from where Discriminant Analysis left and final model provided approximately 75% classification accuracy. Such a figure may seem low compared to similar studies. However the model predicts the deficiency in the capital adequacy, a pre-default event, which is obviously more difficult to predict than default itself.

Tez Özeti

M.K. Tahir Demircioglu, “Finansal Aracı Kurumlar için Nöral Ağlarca Geliştirilen Erken Uyarı Sistemi”

2008 yılında yaşanan finansal kriz mevcut finansal sistemin daha iyi kontrol edilmesini ve daha sıkı kurallarla düzenlenmesi gerektiğini göstermiştir. Doğrudan daha sıkı kuralların uygulanması finansal sistemin maliyetlerini artıracak ve dolayısıyla ekonomik gelişmeye de zarar verecektir. Daha sıkı kuralların maliyetlerini azaltmak için düzenleyici otoritelerin, eskisinden daha komplike olan yeni yöntemleri denemeyi değerlendirmeleri gerekmektedir. Bu tezde Türkiye’deki aracı kurumlar için bir finansal erken uyarı sistemi önerilmektedir. Aracı kurumlara özel olarak geliştirilen model için Diskriminant Analizi ve Sinir Ağları metodları karşılaştırmalı ve tamamlayıcı olarak kullanılmıştır. Metod için kullanılan kapsamlı veritabanı Sermaye Piyasası Kurulu tarafından 1999 ile 2009 yılları arasında tüm aracı kurumların finansal bilgileirni içeren Sermaye Yeterliliği Tabanı raporları kullanılarak oluşturulmuştur. Yazında popüler olan bağımsız değişkenlerin yanında, bu kapsamlı veritabanınının getirdiği avantajlardan faydalanmak için yeni değişkenler de türetilmiştir. Veritabanının önemli varsayımlarını ihlal etmesine rağmen Diskriminant Analiz ile modelin temelini oluşturan bağımsız değişkenler seçilmiştir. Yapay Sinir ağları kullanılarak Diskriminant Analiz ile oluşturulan modelden, %75 oranında doğru sınıflandırma yapabilen nihai model geliştirilmiştir. Bu oran benzer çalışmalara göre düşük görünse de, model iflasa göre tahmin etmesi doğal olarak daha zor olan sermaye yeterliliği tabanında oluşan açığı, yani iflas öncesi bir durumu tahmin edebilmektedir.

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CONTENTS

CHAPTER 1

INTRODUCTION

Fundamental Causes of Recent Financial Crises

Macro trends in the last ten to fifteen years together with financial innovation paved the way for the recent deep financial crisis, so deep that it is compared to The Great Depression of the 1930s in many ways. Oil exporting countries and East Asian countries led by China and Japan have accumulated large account surpluses whereas Western countries led by the US, the UK, Ireland and Spain incurred high current account deficits.

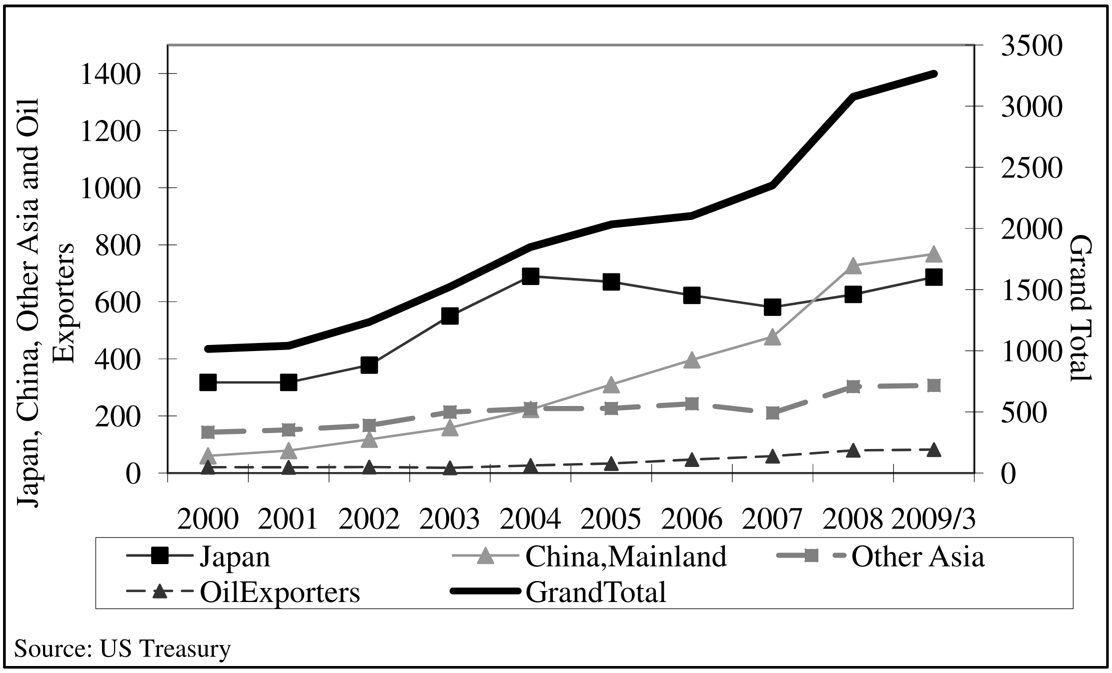
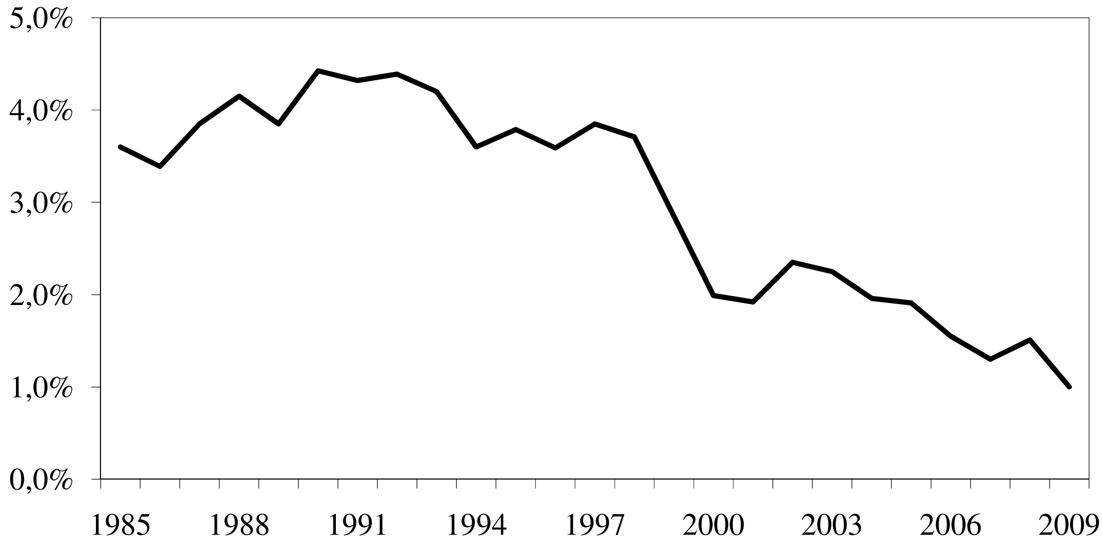


Figure 1: Foreign holding of US debt

Funds accumulated from current account surpluses were heavily invested in risk free government bonds of the developed countries which led to plunge of real interest rates to historical lows.

Low interest rates in turn fuelled the rapid growth in credit extension in deficit bearing developed countries and also spread to some of the emerging markets. Such abundance of financing inevitably resulted in soaring asset prices, including real estate. Assuming that price increases will be sustainable for a longer period, high LTV and low LTI subprime credit became attractive for both the lenders and borrowers. Lenders assumed that sooner or later prices will increase and LTVs will improve, and underlying assets will be resold at higher values in case the borrowers' income is not sufficient to cover the installments.



Source: FSA, Bank of England Calculations

Figure 2: UK real interest rates

Balance sheets of the financial institutions need to grow very fast in order to facilitate such large capital flows; however capital adequacy of the western banks were not strong enough to keep all of the originated loans on their balance sheets. New financial products were developed to meet the higher yield demand of the investors in an era of historically low interest rates. New securitized credit instruments were invented by the financial markets in order to satisfy the savers and borrowers. First, banks or bank like institutions originate subprime or high risk loans, and then pack them as a portfolio. Next, an insurance, i.e. CDS is placed in the pack before sending to the rating agency in order to get an investment grade rating. Such instruments with slightly higher yield are then offered to investors and leave the balance sheet of the banks. Thus, risks of banks are reduced, and balance sheets are freed up for loan origination again. Linking the savers and debtors directly, securitization is supposed to diversify the risk away from the banks.

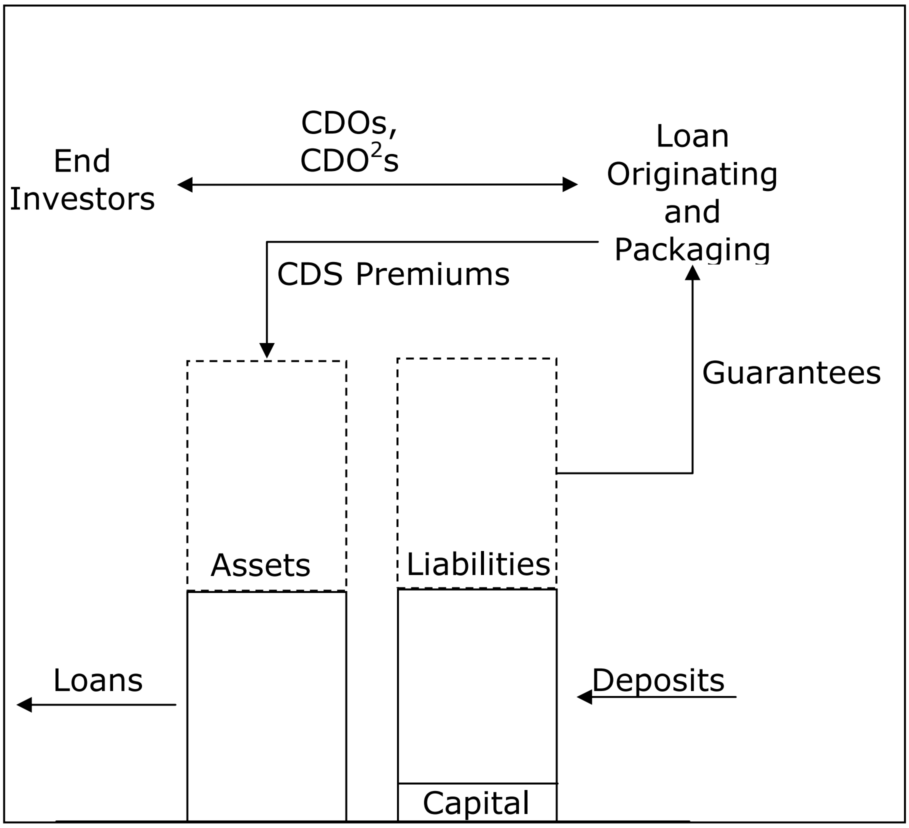


Figure 3: Securitization

Government bonds crowded by the excess funds of the current account surplus bearing countries, a substantial demand developed for higher yield lower risk instruments subsidizing for the government bonds. However, the prime lending market was not large enough to absorb such excess liquidity and the debt markets extended to cover more of the credit hungry subprime market and further leverage the prime market. Investors have driven a ferocious search for higher yield. Large institutional investors like pension funds found twenty-thirty bps additional annual yields for higher risk very attractive. On the other hand, they were not fond of the whole of the extra risk embedded in the high yield instruments and were looking to give up some of the yield to get rid of some parts of the excess risk. CDS like instruments came into the picture to convert these assets to a spectrum with different risks and returns. Such an alignment of incentives created the securitization of low quality credit backed by direct or indirect guarantee of a reputable financial institution in the form CDS, for the purpose of enabling investment grade credit ratings.

However, when crisis was triggered by the defaults in the United States sub-prime market, the picture was not as it was intended to be. Banks, who were supposed to have sold the credit risk, were actually still carrying it in the trading books. Banks bought the greasy insurances that were put on the credit packages from the secondary market or indirectly provided guarantees to the credit packs sold through subsidiaries. One of the driving forces behind such an action of the banks were the search for additional income, as profits of the banks shrunk with the falling interest rates. Such system also aided in the creation of investment grade instruments from low quality assets. Although the risk was supposed to be diversified away through believed-to-be-liquid instruments like CDS, they actually never left the balance sheets.

Despite securitization, leverage of the banks increased significantly as the sizes of the balance sheets inflated in order to keep up with the booming economic activity. Other than securitization, “Special Investment Vehicles” (SIVs), which were offshore subsidiaries, were also utilized for balance sheet make up, that allowed banks to have subsidiaries with little capital and large debt. Although banks did not officially back up the obligations of the SIVs when the crisis broke, they took the dive for the sake of reputational issues or political pressures anyway.

The market pressures pushed the solution to find its way through the cracks in the system. Risk was not diversified but transferred from the loan books of banks, where capital adequacy requirement is tighter and closely monitored by the regulators, to the trading books, in the form of CDS or similar instruments where capital adequacy is much lower, and monitoring is much more difficult. Regulations were looser for the trading books counting on the liquidity of the products traded and also due to the complexity of the instruments.

Defaults led to downgrading of the securitized credits, which subsequently triggered forced liquidation of positions and eventually created a liquidity crisis where large volumes of securities were forced for sale and no buyer had the money to bid for the degraded instruments. Pressure on the financial system sourced by the need to process high volume of funds and inventions to satisfy the excessive demand for high yield low risk instruments created a procyclical structure in the financial markets.

Although most of the industry experts and regulators were aware of such phenomena, it was believed that the ongoing financial evolution was sustainable as presented below in the phrase from the IMF Financial Stability Report, which outlays the expected result from an ideal securitization scheme. However, the reality was slightly different, financial institutions were providing guarantees on such disposed securitized assets through instruments like CDS. Only the custodian of the assets was changed most of the time, assets were held by the investors instead of sitting on the balance sheets of the banks. The risk, on the other hand was still with the banks, just transferred from loan books to trading books.

> There is growing recognition that the dispersion of credit risk by banks to a broader and more diverse group of investors, rather than warehousing such risk on their balance sheets, has helped market he banking and overall financial system more resilient…
>
> The improved resilience may be seen in fewer bank failures and more consistent credit provision. Consequently the commercial banks may be less vulnerable today to credit or economic shocks. (IMF Global Financial Stability Report, April 2006)

It was also assumed that market forces will bring market discipline more effective then regulations, if a product is not justifying its risk or return, general self correcting markets were supposed to deal with it accordingly. Banks were meeting their capital adequacy ratios with their smaller balance sheets, investors had their low risk but slightly higher yielding assets and the senior management of the banks received large bonuses as banks became more profitable through trading CDS like instruments. As long as there was profit, bank managers seemed successful and did not need to truly understand or interfere with the profitable business, and also took comfort from the fact that most of the industry was also acting in the same direction.

Regulatory bodies had adopted the philosophy that protection of the end customers can be achieved by ensuring the transparency of the large institutions and financial products. Such efforts were also underpinned by the rating agencies, which endorsed the creditworthiness of institutions and the products they sell without truly analyzing the big picture. Further, transparency is also jeopardized by opaque and complex structure of the trading books and behind irrational confidence in liquidity.

Beliefs on the well diversified overall risk of the system, unfortunately, were not the case in reality.

Last but not least, large multinational financial institutions with cross border operations were not easy to monitor and regulate. Independent from whether they were running operations through their subsidiaries or branches in foreign countries, the regulatory power somehow remain with the home country authority. Such complex corporate structures were very difficult to monitor, especially when off shore booking of risks on the balance sheets of a number of different subsidiaries further put shadow on the corporate structures.

New Measures

Nowadays, multilateral organizations and national regulators are working on a new scheme of regulations in order to avoid another financial meltdown in the future (Turner Review, 2009). Such regulations are still being worked on, and being negotiated on a multinational level among the regulatory bodies. However, there is a clear consensus on two issues. First, the monitoring and requirements shall be tighter. Second, there shall be an international coordination in order to effectively regulate cross border operations of large banks, together with the idea of creating a level playing field for all institutions.

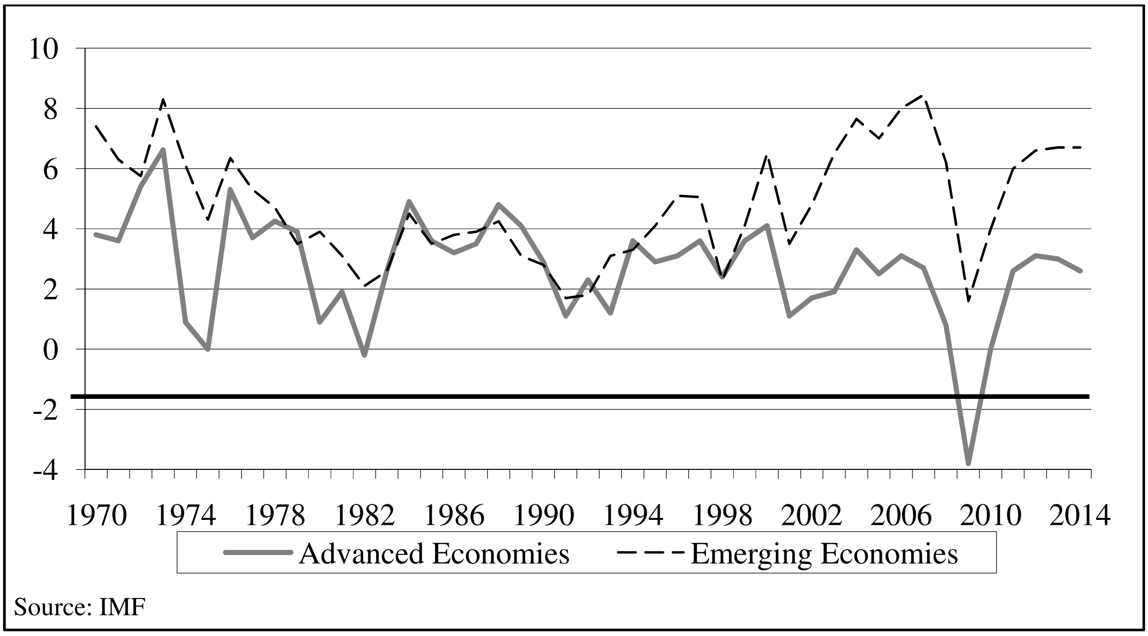


Figure 4: Real interest rates

A new system will be looking for a balance between tighter regulations and the respective cost of such to the financial services. As the regulations become tighter, the cost of financial services will be higher and eventually hurt the economic growth for the sake of lower default risks. On the other hand, looser regulations will bring the costs down and fuel growth but lead to higher default risks and unsustainable growth. The recent financial crisis seems to tip the scale in the favor of tighter regulations.

Lessons learned from the financial crises of 2008 is now leading to tighter financial regulations which will considerably decrease the default risk of the financial system and contribute significantly to sustainable growth. In the next decade expecting higher credit margins, and lower LTV or LTC ratios than the past five years is not unrealistic, however, together with lower growth rates.

Commercial banks will face restrictions in trading activities and will focus on their primary mission of intermediation of credit flow to real economy. Trading, which is essential for the liquidity of financial markets may be handled by other financial institutions that do not have access to saving deposits in order to keep the commercial banks from away from the exposure to trading risk. Broker dealers, investment banks and similar financial institutions will be among those that facilitate more of the trading function besides their role for the intermediation of the equity capital.

In an era of higher credit margins and lower appetite for credit risk, importance of access to equity capital markets will increase where private sector will be required to supply more equity to finance investments. The role of the broker dealers in the real economy will increase, as the importance of raising equity capital becomes more critical.

The credit margins on the other hand, will increase due to both increased costs of higher level of required expensive bank capital and cost of funding, making the scarce debt more expensive. The difference shall be made up by the equity, both in terms of cost and amount in order to keep up with the global competition going forward. Broker Dealers and investment houses shall operate more efficiently and provide access to equity capital in a cost effective and reliable fashion.

Turkey and Intermediary Institutions

Turkish economy, which was in a rapid expansion phase since 2002, was profitable enough for the local banks to keep them away from the financial scheme that led to crisis. The capital adequacy ratio requirement of the Banking Regulatory and Supervisory Authority is quite high since the 2001 crisis, which is 17,5%, more than double of that of developed countries, which is approximately 8%. As of December 2008, none of the 49 banks in the Turkish financial system had capital adequacy ratios below 12%. However, although the banking system is not hurt in the recent crisis, a significant portion of the funding of banks is sourced from foreign financial institutions in the form of syndication loans or other swap instruments. As foreign financing will decrease and the tighter covenants in the renewed loan agreements require Turkish banks to be more risk averse and credit extending capability will eventually be affected. Further, direct lending from foreign banks to Turkish economy will also decrease, as foreign banks will first try to meet the credit demand in their home country.

Regulation of the Intermediary Institutions consequently will become more important. The system shall ensure that their operations are reliable and sustainable, in order to provide the end investors with sufficient confidence. Investing in equity capital is already bearing more risk than investing in saving deposits or government bonds, and therefore there is not much room for extra risk in the intermediation. Also, companies looking to raise equity shall also be able to depend on the system in order for them to construct long term investment plans and strategies.

In order for Intermediary Institutions to operate in a cost effective manner and provide access to equity capital at the lowest cost possible, the balance between the default risk and the expensive regulatory capital shall be set with care. High capital requirement to control the default risk will eventually increase the costs of these institutions, which, in an era where the cost of debt is increasing, will further hurt the overall financing costs of the companies. For the sake of decreasing the cost, looser regulations may increase the default risk and shake the confidence which will be very hard to rebuild. Moreover, setting high requirements may also hinder the competition, by increasing the entry barriers. All these factors underline the importance of well balanced regulations for the healthy functioning of the industry.

The purpose of this study is to develop a financial early warning system for Intermediary Institutions to be used for determining the right balance between cost and risk, and provide the regulator with the opportunity to interfere and control the risk in a timely fashion and consequently minimize the default risk at a reasonable cost.

CHAPTER 2

LITERATURE REVIEW

Eiteman (1933) proposed that broker's borrowing both from banks and their customers shall be regulated at the same time and extension of credit to speculators is always essential in order to provide liquidity to the market. Loose regulations can easily lead to speculative bubbles which in turn result in a stock meltdown. Broker's liquidity shall also be regulated in order for them to meet the cash withdrawals of their customers without risking their operations.

Beaver (1966) chose prediction of failure to test usefulness of financial ratios which is one of the first studies in prediction through financial ratios, At the turn of the century, the only one ratio used to assess credit worthiness was the current ratio. For the purposes of the study "failure" was defined as the inability of a firm to pay its obligations as they mature. Operationally, a firm was identified as failed when bankruptcy, bond default, overdrawn bank account or non-payment of a preferred stock dividend take place. The purpose was not to identify the causes of failure but to show the usefulness of financial ratios as predictors of important events such as failure.

Moody's Industrial Manual was the most appropriate source for the data of failed companies, although it mostly consisted of larger corporations that were publicly held and did not include non-corporates, privately held companies and non-industrial firms. Such a choice introduced a selection bias as the dataset was formed from larger companies where occurance of defaults were much rare than it was in smaller companies. Despite this flaw, the database represented almost 90% of the capital invested in the

United States manufacturing industry including all sources of capital as forms of debt and equity.

From the dataset, seventy-nine failed firms were identified which had financial statement data available for the first year before failure in the analysis period from1954 to 1964. Failed firms were then classified according to industry type and asset size. A Non-failed firm for each of the failed firms was then matched according to the industry type and asset size. The reason for selecting industry type and asset size as matching pairs was simply the fact that the same ratios may have different implications for different industries and for companies with different asset sizes.

In order to get a close match in terms of asset size, where its importance was emphasized significantly, pairs were allowed to be from different time periods. For example, a failed firm in 1963 was matched with a firm that has a similar asset size in 1955. The financial statements of failed companies were collected for five years prior to failure and matched with non-failed companies that have similar asset sizes for five consecutive years. Thirty ratios were computed into six “common element” groups which were selecte among the popular ones in literature and the ones that performed well in previous studies.

Group 1 (Cash Flow Ratios)

1) Cash flow to sales

2) Cash flow to total assets

3) Cash flow to net worth

4) Cash flow to total debt

Group 2 (Net-Income Ratios)

1) Net income to sales

2) Net income to total assets

3) Net income to net worth

4) Net income to total debt

Group 3 (Debt to Total-Asset Ratios)

1) Current liabilities to total assets

2) Long-term liabilities to total assets

3) Current plus long-term liabilities to total assets

4) Current plus long-term plus preferred stock to total assets

Group 4 (Liquid-Asset to Total-Asset Ratios)

1) Cash to total assets

2) Quick assets to total assets

3) Current assets to total assets

4) Working capital to total assets

Group 5 (Liquid-Asset to Current Debt Ratios)

1) Cash to current liabilities

2) Quick assets to current liabilities

3) Current ratio (current assets to current liabilities)

Group 6 (Turnover Ratios)

1) Cash to sales

2) Accounts receivable to sales

3) Inventory to sales

4) Quick assets to sales

5) Current assets to sales

6) Working capital to sales

7) Net worth to sales

8) Total assets to sales

9) Cash interval (cash to fund expenditures for operations)

10) Defensive interval (defensive assets to fund expenditures for operations)

11) No-credit interval (defensive assets minus current liabilities to fund expenditures for operations)

One ratio from each of the six groups was selected and the means were compared, where all of them were in line with the theoretical prediction. Next, a dichotomous classification test was undertaken, all of the companies are sorted by each of the thirty ratios and a cut-off point was selected where the firms above (below) the cutoff are to be classified as failed and firms below (above) the cutoff point are to be classified as non-failed. Cut off points were selected to minimize the misclassification. The sample was divided randomly into two subsamples, one of them was used to determine the cut-off points and the other one was used to test their validity or predictive ability. The ability to predict failure showed the strongest prediction of failure based on the misclassification percentages. It was also concluded that as years to default increases, the predictive power of ratios deteriorates.

Next the histograms of the ratios were analyzed and it was observed that failed and non-failed firms could be distinguished despite some overlap, where such overlap increases as years to default increases. Also from the skewness of histograms, non-normality was suspected and test of normality through density function clearly demonstrated the non-normal distribution of the financial ratios. Non-normality makes it difficult to run a multivariate analysis, as most of the multivariate techniques require normal distribution of the data.

Beaver (1968a) tried to provide an emphasis on empirical verification of *a priori* beliefs and to illustrate a method to empirically evaluate alternative accounting measures. Commonly used ratios for prediction of failure including liquid asset ratios and non-liquid asset ratios was analyzed. It was predicted that non-liquid asset ratios are better predictors three or four years prior to failure, whereas liquid asset ratios are better in doing the job in one or two years prior to failure. Window dressing of the companies and misleading structure of some of the ratios, i.e. ones assuming inventories as liquid assets in some cases, may lead to misdirection. The data for seventy-nine failed and seventy-nine non-failed firms were selected with the same method used in the Beaver (1966) study. Using three non-liquid asset financial ratios, four asset to total asset financial ratios, three liquid asset to current debt ratios and four liquid asset turnover ratios, companies in the dataset were sorted and a cut-off point was determined by trial and error that minimizes the misclassification, similar to the Beaver (1966) study. Results showed that non-liquid asset ratios were better in discrimination of failures and non-failures than liquid asset ratios in all five years prior to failure. Beaver proposed that such difference was due to window dressing, where non-liquid asset ratios were much difficult to alter, contrary to liquid asset ratios. Also, quick assets ratio and current asset ratios were doing worse than cash ratios, which was again contrary to literature. It was proposed that, as a ratio becomes popular, managements pay much more attention to that ratio and perform window-dressing resulting in loss of predictive power. Analysis of the ratio components revealed that, failed firms tend to have less cash and more accounts receivable which may explain why cash did better than quick assets and current assets. Also failed companies had less current assets but more current debt, as expected. Another unexpected result was the lower inventory level of failed companies.

Beaver (1968b) also used the dataset that contained seventy-nine pairs of failed and non-failed companies of the Beaver (1966) study to include the market price changes in the analysis of failure prediction. Market returns were matched with financial statement announcement dates, which were assumed to be at the seventeenth week following the end of fiscal year. In line with the expectation, as failure approaches, return on the failed companies became lower than non-failed ones, and the largest increase difference one year prior to failure. When the companies were sorted according to the returns and a cut-off point was selected to distinguish between failed and non-failed companies, it was shown that cash flow to total debt was a better predictor than returns. However, when failed companies were analyzed without any non-failed firms through looking for sharp drops in the market price, it was shown that market prices predict failure sooner than financial ratios. It was concluded that investors use ratios in their decision making process besides some other sources of information and taking this analysis to a multivariate context may have a fruitful potential.

Altman (1968) introduced multiple discriminant analysis in order to enhance the simple company ratio comparisons, which was criticized by theorists although widely used by practitioners. All studies prior to this paper discussed ratio analysis in a univariate context, and cited a different ratios as being the most important. Thus, adaptation of these results for assessing companies was questionable both theoretically and practically. Ratio analysis presented in this fashion was rightfully called susceptible to faulty interpretation and was potentially confusing. It was proposed that detecting the important ratios and the degree of importance of them to form a meaningful model may bring the necessary insight to the promising ratio analysis. Multiple discriminant analysis was used successfully in the financial problems such as consumer credit evaluation by Durand (1941) and investment classification by Myers and Forgy (1963) prior to this study.

Sixty-six companies with equal number of bankrupts and non bankrupts were selected among manufacturing companies and matched on a stratified random basis for the period between 1946 and 1965. The firms were stratified according to industry and size, and the data collected for non-bankrupt firms were from the same years as those compiled for the bankrupt firms. Twenty-two ratios were computed from the income statement and balance sheets, which were based on the successful ones on previous researches and ones with potential relevancy to this study.

Five ratios out of twenty-two were selected on the basis of, (i) statistical significance of various alternative functions, (ii) inter correlation between relevant variables, (iii) predictive accuracy of various ratio profilers, and (iv) judgment of the analyst:

1) Working Capital / Total Assets
2) Retained Earnings / Total Assets
3) Earnings before interest and taxes / Total Assets
4) Market Value of Equity / Book Value of Total Debt
5) Sales / Total Assets

The final discriminant function was as follows:

$$Z = 0{,}012\frac{Working\ Capital}{Total\ Assets} + 0{,}014\ \frac{Retained\ Earnings}{Total\ Assets} + 0{,}033\frac{EBIT}{Total\ Assets} + 0{,}006\frac{Market\ Value\ of\ Equity}{Book\ Value\ of\ Debt} + 0{,}999\frac{Sales}{Total\ Assets}$$

The cut-off Z score was determined as 2,675 based on the number of correct predictions by each cut-off point.

In order to judge relative importance of each ratio, the ratios were observed as a scaled vector which was computed by the square roots of the diagonal elements of the variance-covariance matrix. The statistics showed that EBIT to Total Assets ratio was doing the best job in discrimination followed by Sales to Total Assets. This was surprising as Sales to Total Assets had the lowest discriminating power on univariate basis. The reason for this was stated as the strong negative correlation of -0,78 between EBIT to Total Assets and Sales to Total Assets. Relative contributions of the variables were given as:

Variable	Scaled Vector
Earnings before interest and taxes / Total Assets	9,89
Sales / Total Assets	8,41
Market Value of Equity / Book Value of Total Debt	7,42
Retained Earnings / Total Assets	6,04
Working Capital / Total Assets	3,29

The results were very satisfactory. Using financial data one year prior to bankruptcy only resulted in two misclassified bankrupts and one misclassified non-bankrupt, which translates to 95% overall accuracy. As expected the overall accuracy deteriorated to 72% when ratios two years prior to bankruptcy were used.

In order to check the reliability of the model, five random selections of sixteen firms were used to construct the models and the rest was left as holdout samples. Average accuracy was 93,5%, which showed that the model was quite reliable. Also, a secondary sample of twenty-five bankrupt firms was tested with the discriminant model, and the results were even better than the first model. Another secondary sample of sixty six non-bankrupt firms with admittedly below average performance was selected and 79% of these were correctly classified. The misclassified firms which were referred as "temporarily sick" were among the ones that posted negative profits and lied in the overlap area (or gray area) between bankrupts and non-bankrupts.

Checking for the long-run predictive accuracy, it was found that predictive accuracy substantially diminished after two years, and it was shown that all ratios deteriorate as bankruptcy approaches where most of the deterioration happen during the period between two and three years prior to bankruptcy.

Meyer and Pifer (1970) analyzed failure of banks in US and divided the factors explaining bank failures into four groups: (i) local economic conditions (ii) general economic conditions (iii) quality of management and (iv) integrity of the employees. Dates regarding local economic conditions were not available. However this factored in through pairing closed banks with solvent banks in terms of location, similar size and age and same regulatory requirements. Data for a solvent bank also covered the same period as its matched closed bank. As both closed banks and solvent banks data are from the same period, effect of general economic conditions are supposed to become insignificant as it affects both groups in the same way, therefore general economic condition variables were not included in the subsequent analysis. Quality of management and integrity of the employees could not be assessed easily. However such were assumed to be mirrored in the balance sheet and the income statement data eventually. Therefore selection of the independent variables from readily available financial statement data was proposed to complete the model.

The sample included failures from the 1948 to 1965 period, where thirty-nine closed and thirty-nine solvent banks were identified that had six years of financial data prior to failure of the closed bank. The dataset was then divided to two parts, the derivation sample with thirty pairs and the holdout sample with nine pairs. Twenty-eight operating ratios and four balance sheet levels were selected for analysis. A stepwise regression program was used which combined forward selection and backward reduction.

Regression was run for the independents from one year and two year prior to failure and yielded five to nine variables for each year. Models with three and more years prior to failure were not very successful in discrimination. R^2 and F values for both one year and two year prior to failure data and models with different numbers of variables were all significant at the one percent level. The signs of most of the variables corresponded with the a priori expectations. However, half of the variables explaining the variance in one year and two year failure were different.

With five variables, the misclassification rate was 25%, and nine variables lead to only 12% misclassification for the original sample of one-year to failure group. The misclassification rate of the original sample of two-year to failure group was substantially higher. An interesting observation was that misclassification of closed banks were higher with the two years to failure data, but the opposite was true for solvent banks, which showed that immediately prior to failure, the factors causing failure also effected the solvent banks. The average percentage of errors in the holdout and original sample were not significantly different. With one year to failure data, and with any number of regressors, 83% of the banks in the holdout sample were correctly classified. As expected, model with two years to failure data, posted more misclassifications. It was also proposed to select the cutoff point that minimizes the costs from the regulatory agency perspective. Setting the cutoff point too high could result in classification of almost all of the failing banks correctly, however at the cost of higher misclassifications of solvent banks as failing banks. The regulatory agency may determine the optimum cut-off point based on the cost of resources it may allocate to prevent failure through intervention.

Deakin (1972) aimed to propose an alternative model to Beaver (1968) and Altman (1968) for the prediction of bankruptcy. First Beaver (1968) study was replicated with the fourteen ratios but with a sample from 1964 to 1970. Thirty-two failed firms were identified where failure was defined as bankruptcy, insolvency and liquidation for the benefit of creditors. Each of the failed firms was matched with a non-failed firm on the basis of industry classification, year of the financial information provided and asset size. Dichotomous classification tests confirmed the results of Beaver. Results also showed that the failed firms tended to expand rapidly in the third and fourth years prior to failure. A closer look revealed that such failed companies were invested in plant and equipment and financed these investments with debt.

For the discriminant analysis a randomly drawn sample of non-failed thirty-two firms was used due to concerns presented by Tatsuoka (1970 and 1971). The constructed discriminant function with fourteen variables yielded the best results. Trying to decrease the variables based on their contributions led to substantial increase in misclassification. Discriminant function was computed for each of the five years prior to failure separately, where the relative importance of variables changed over the years. The significance of the discriminant function was then analyzed by Wilks' lambda which can be converted to an F Value. The discriminant function was significant at 0,001 level for the first two year, at 0,01 level for the fourth and 0,05 for the fifth year revealing that up to three years prior to failure, the failing companies can be classified accurately. Discriminant results showed 3%, 4½%, 4½%, 21% and 17% accuracy for the years one through five years prior to failure respectively. It was apparent that the discriminating power was diminishing after three years.

Validation was performed through selecting a random sample of eleven failed and twenty-three non-failed firms. The misclassification rates were 22%, 6%, 12%, 23% and 15% respectively for the years one through five prior to failure. Although a drop in the results was expected, the deterioration in the first year prior to failure did not have a justifiable explanation. Then the functions derived for the first three years were tested on a sample of failed firms, whose failure was to happen in the next five years and for non-failed firms who were not to fail in the next five years. Total misclassification rates were 13%, 10% and 18% for one to three years prior to failure respectively. The function that was derived with data two years prior to failure was the best performer which also had the highest significance among other functions.

Altman (1973) emphasized the long lasting financial problems of the United States railroad industry and the need for a financial early warning system. The major reasons for the poor financial performance of the railroads were identified as (i) the inability to meet competitive conditions due to an inflexible pricing and cost structure, (ii) the vulnerability during periods of economic downturns due to its fixed asset structure and high leverage, (iii) excess capacity, (iv) labor and manpower rigidities and (v) shortage of innovative management, where many of them were sourced from government regulations and industry rigidities.

One of the advantages of the study with respect to similar ones in the literature was that all companies were from the same industry, thus creating a nice homogeneity in terms business lines and operations of the sample in constructing the model and the testing phase. Another advantage stemmed from the ICC reporting requirements, which enabled access to a comprehensive database for present and past financial statements. Another unique characteristic of the industry is the highly regulated operating environment.

A group of twenty-one railroads that went bankrupt during 1939-1970 were selected, which had sufficient data and comprised of Class I railroads, where revenues exceed five million dollars. Balance sheet and income statement data were gathered for the first and second years prior to bankruptcy. Moody's also published extremely comprehensive industry data on annual bases, and financial statistics for the industry was gathered as a whole for the same years that bankruptcy data was present. Then the following ratios were selected based on those found to be meaningful in the past studies, popularity in literature and those thought to be particularly relevant to the railroad industry:

A. Liquidity Measures:

1) Net Current Assets / Total Assets

2) Net Current Assets / Total Operating Revenues

B. Profitability and Efficiency Measures

3) Income before Interest and Taxes / Total Assets

4) Operating Revenue / Total Transportation Property

5) Operating Revenue / Net Transportation Property

6) Operating Expenses / Operating Revenue

7) Transportation Expenses / Operating Revenue

8) Income after Taxes and Fixed Charges / Operating Revenue

9) Total Maintenance / Total Transportation Property

10) 3 Year Compound Growth Rate of Operating Revenue

C. Solvency and Leverage Measures

11) Earned Surplus (Balance Sheet) / Total Assets

12) Total Debt / Total Assets

13) Fixed Charges Earned (Before Taxes)

14) Cash Flow / Fixed Charges

Average of ratios were calculated by assigning proportional weighting to the number of companies that went bankrupt during the period, i.e. if two companies went bankrupt in a given year, that years' averages were weighted by 2/21 in order to remove any bias due to trend movements, as the bankruptcy dates of firms were spread to a long period of time. As expected all of the ratios of the bankrupt firms were worse than the industry averages and worsen for the first year prior to bankruptcy with respect to second year prior to bankruptcy. Ratios fourteen, seven, eleven, ten, eight, six, three were elected to be included in the discriminant analysis model and the ordering of these seven variables was derived from the discriminant analysis program that ranked these variables in terms of contributory importance. The discriminant model was as follows:

$$
\begin{aligned}
Z = 0{,}2003\,\frac{Cash\ Flow}{Fixed\ Charges} - 0{,}2070\,\frac{Transportation\ Expenses}{Operating\ Revenue} \\
+ 0{,}0059\,\frac{Earned\ Surplus}{Total\ Assets} \\
- 0{,}0647\,(3\ year\ Compound\ Growth\ Rate\ of\ Operating\ Revenue) \\
+ 0{,}1040\,\frac{Income\ after\ Taxes\ and\ Fixed\ Charges}{Operating\ Revenue} \\
+ 0{,}0885\,\frac{Operating\ Expenses}{Operating\ Revenue} \\
+ 0{,}0688\,\frac{Income\ before\ Interest\ and\ Taxes}{Total\ Assets}
\end{aligned}
$$

The group means of the two group railroad sample were -3,640 for bankrupts and +0,299 for industrial average. It was noticeable that liquidity measures did not enter the final profile of variables in the discriminant analysis, as they were promising on univariate basis. In the calculation of the Z scores, all ratios entered as percentage values, e.g., thirty-five for 35% where the only exception is Cash Flow to Fixed Charges which entered as number of times. One year prior to bankruptcy results were very accurate with only one misclassification of bankrupts as non-bankrupt and non misclassification of industry averages. Two year prior to bankruptcy results were also the same, where the same observation was also misclassified. An interesting observation was that Z Scores of seven firms did not deteriorate which showed that the Z score of a firm was not necessarily deteriorating as bankruptcy approaches.

Another model was constructed, this time using paired non-bankrupt firms instead of industry averages as industry averages and individual firm values may differ if the standard deviation is high. However, the second model also yielded quite accurate results, this time the scores of bankrupts and non-bankrupts were more packed compared to previous model. Z-Score mean was -0,164 for non-bankrupts and -2,695 for bankrupts and the overall accuracy was 92,9%, where two non-bankrupts and one bankrupt were misclassified.

Next the original model is tested for validity through constructing five samples with eleven bankrupts in one sample and ten bankrupts in the other: The first model was constructed with all odd numbered railroads and their associated industry average, second model was constructed with all evens plus number one, third model was constructed with random selection, fourth model was constructed with first eleven observations and fifth model was constructed with last eleven observations. Percent of correct classifications in the validation samples were, 85%, 95%, 90%, 80% and 65% respectively for the five models described. Statistical tests showed that the validation results substantiates that the models possessed significant discriminating power on observations that are not used to establish the parameters of the model.

Another validation test was done through selecting fifty railroads from 1946 to 1969. Then the Z-Score of the original model was applied and six firms were classified as bankrupt. Two of these actually went bankrupt subsequent to the test, one discontinued all railroad operations, two others merged into larger railroad systems, both of which have actually gone bankrupt. Although the model was very accurate in predicting non-bankrupts, the validation of this in the fifty railroad random sample was not easy. However, no obvious short term error was spotted. Next, the actual sample is tested with the model and out fifty-five railroads fourteen appear to be potential bankrupts. Six out of these fourteen were actually in the bankruptcy phase, five out of the remaining were the ones designated by the analysts as possibly on the brink of failure, and the remaining three was controlled by larger more solvent railways which might explain their non-bankruptcy legal position.

Altman (1974) developed a model for determining credit worthiness of commercial loans in the cotton and wool textile sectors in France. Repayment performance of thirty-five problem firms and ninety-nine good firms were analyzed for the 1968-1971 period. At the date of the study, a commercial bank passed a loan request of a company to Banque de France for evaluation. Based on the evaluation, the government guarantees the loan and the commercial paper was accepted in the money market. If not, the bank could still extend the credit at its own risk.

The sample of good textile companies was comprised of firms matched to the problem sample by size and year. Although this provided a relatively homogeneous sample of firms with financial statements over a short time span, financial statements were limited two years, which made the trend analysis meaningless. Forty-one financial ratios for the sample of 134 companies were computed and categorized by liquidity, indebtedness, profitability, turnover, coverage and value added.

In univariate analysis, liquidity ratios showed a fair degree of overlap. Leverage ratios also showed moderate discriminating power. Activity ratios showed that a longer collection period was associated with good firms, which showed that the tolerance for longer period was a sign of strength. Most of the operating ratios also showed little discrimination, however profitability and cash flow ratios were promising.

Next a principal component analysis was run and only two components containing 40% of the information content of the forty-one ratios were extracted. One of the dimensions resembled the relative importance of the investments in the firms. The other dimension seemed to measure the importance of cash flow but independent from the importance of investment, which was finally interpreted as a measure for relative importance of margins. The two dimensional plot with respect to these variables showed some discrimination but also a fair overlap.

The discriminant analysis with all forty-one ratios revealed 14% misclassification in problem companies and 1% in good companies when one year prior to default data were used. Such ratios deteriorated to 22% and 2% respectively when two year prior to default data were used. A reduced model was also formed by inferences from the principal component analysis and correlations of variables. Ten variables were determined as best discriminators:

1) Long Term Debt to Permanent Funds
2) Equity to Total Debt
3) Permanent Funds to Short Term Debt
4) Equity to Sales after Taxes
5) Receivables and Discounted Notes to Sales After Taxes

6) Sales after Taxes to Total Assets
7) Total Fixed Assets to Depreciation
8) Value Added to Production
9) Wages plus Salary to Value Added
10) Gross Profit to Equity

These ten variables were from leverage, profitability and value-added. However, overall discriminant strength was down to 62% from 81% of the model with 41 ratios. An efficient use for practice was proposed as dividing the companies into three subgroups instead of two, and conducting a deeper analysis for the ones that are in the middle area or gray zone.

Blum (1974) analyzed the predictive accuracy of the Failing Company Model, which was related to the antitrust laws. A failing company could merge with a competitor if there was not another good faith buyer. 115 failed companies during the 1954 to 1968 period were matched with non failed pairs in terms of industry, sales, employees and the fiscal year. Data were gathered for eight fiscal years, if available. The range of years "one to three before failure" was thus the most recent time period for both failed and non-failed firms. Since the minimum time period for analysis was three years, there was a maximum of twenty-one possible ranges of years.

Each range was divided into two, where one part was for derivation of the model and the second part was left for validation. Although this study was also predicting failed companies, the costs of misclassification were much more different for the purposes of this study. Allowing non-failing firms to complete mergers because of their mistaken description as failing firms may hurt the interests of the public more than sending genuinely failing firms to their liquidation after bankruptcy proceedings.

The Failing Company Model predicted the failed companies to fail and non-failed companies to not to fail with an accuracy of 93% to 95% at the first year before failure. Predictive accuracy was 80% for the second year before failure and 70% for the third, fourth and fifth years before failure, with validation samples showing plus and minus 3-5% accuracy.

Libby (1975) performed a study designed to determine whether accounting ratios provide useful information to loan officers for the prediction of business failure. In the experiment, loan officers predicted business failure from a small set of accounting ratios and their performance was measured in terms of accuracy of the predictions. Consistency was measured within loan officers decisions over time and between loan officers. Agreement over time was measured over immediate and one-week intervals.

Loan officer participants were drawn from two subpopulations of seven small and five large banks, a total of sixteen and twenty-seven loan officers was selected from small and large banks respectively. The loan officers differed in experience, age and rank among groups; however the client base of the large banks had significantly larger asset sizes. Due to this difference, small bank loan officers claimed that large bank officers will outperform them as large bank loan officers base more of their judgments depending on the audited financial statements of large corporations where financial analysis was more intensely performed.

Large bank officers were split into two groups, where one group evaluated financial statements of seventy companies in one week and the other half evaluated thirty in the first week and forty in the second. The sample had ten repeat companies following the first thirty companies every four company. The second sample also had these ten repeat companies in the same manner in their second week of evaluation. Due to limited number of small bank officers, they only evaluated seventy statements in one week. Each officer was asked to predict failure within the next three years and state their confidence on a three point scale.

Sixty firms were drawn at random from the Deakin (1972) sample and fourteen ratios of Beaver (1968) and Deakin (1972) were then computed for one of the three years prior to failure at random that resulted in an equal number of firms for each of the three years prior to failure. Next a principal component analysis with varimax rotation was done and the resulting dimensions were profitability, activity, liquidity, asset balance and cash position. Through analysis of the rotated matrix, net income to total assets, current assets to sales, current assets to current liabilities, current assets to total assets, and cash total assets were chosen respectively to represent the five dimensions. Then discriminant analysis was run and the predictive ability of the fourteen variable and five variable models were compared based on derivation sample and double cross-validation. Five variable sample performed slightly worse, as expected, in both derivation sample and cross validation.

All but three of the loan officers predicted failure better than chance and the average was forty-four correct predictions despite the trend and industry data was not available to the participants. 74% correct predictions under this circumstance concluded that traditional ratio analysis for credit rating can be justified. Also the test-retest reliability analysis showed that the loan officers were consistent in decision making in terms of agreement over time. From the agreement between subjects point of view, loan officers interpreted the accounting data fairly uniform. Results showed that accounting data was indeed very useful in predicting bankruptcy where bankers with different backgrounds made highly accurate and reliable predictions of failure. However, discriminant analysis results were better.

Joy and Tollefson (1975) discussed the methodology, development and testing of discriminant analysis and other dichotomous classification models and their applications in general, not in particular to financial default prediction. The majority of the financial studies that employed discriminant analysis were criticized for not checking for the pre-requisites, i.e., multivariate normality and equality of variance-covariance matrices with appropriate tests. Financial studies were determined to be more concerned with usefulness of the results rather than optimality.

Financial distress prediction studies were criticized for using samples that did not represent the population. For example, Edmister's (1972) study which used SBA loan records were criticized for not including the data of the companies which were not granted loans. Also it was stated that sample sizes shall also be in proportion to that of the population. Further, it is proposed that there should be a time-coincident validation sample with the same time dimension of the analysis sample for ex-post validation and an holdout sample with data collected from the period that precedes the validation sample to test the predictive power of the analysis, which almost all of the bankruptcy prediction literature lacks.

Another criticized point was the assessment of the relative importance of the independent variables. The method used by Moesteller and Wallace (1963) was proposed to be an appropriate method, which led to significant changes in ranking of the variables in terms of importance of the Altman (1968) study. Also the reported classification results were investigated and the fraction of correct classifications across post-classification groups were proposed as better measures contrary to the fractions reported as correct and incorrect classifications of a given group. Such proposed classification statistics were proposed to make better sense in terms of practical implications which was the ultimate intended final purpose of bankruptcy prediction studies.

It was also stated that the cut-off score shall be proportional to the number of group members in the population. Such proposal may have basis from a statistical point of view but did not really make sense from the bankruptcy prediction perspective. Also a Bayesian approach that accounts for the costs of misclassification was proposed as a better approach for bankruptcy prediction where costs of misclassifying a bankrupt as non-bankrupt were quite higher than misclassifying a non-bankrupt as bankrupt.

Sinkey (1975) worked on an early warning system for the banking industry in the United States which is under the supervision and insurance of FDIC. The “problem banks” sample consisted of two hundred banks with approximately four billion dollars of deposits that had constantly updated data. Out of these two hundred banks, failure rates were relatively low, only sixty-six of them failed during 1959-1973. The problem banks sample of the study consisted of ninety banks identified in 1972 and twenty identified in the beginning of 1973, totaling a hundred and ten problem banks. Each problem bank was than matched with a non-problem bank on the basis of (i) geographic market data, (ii) total deposits, (iii) number of banking offices and (iv) Federal Reserve membership status. The final sample was close enough to be called representative of the total population in terms of size and branch structure.

The independent variables or financial ratios were extracted from the year-end financial statements for the period between 1969 and 1972. The problem banks identified in 1972 and 1973 were non-problem banks during 1969-1971. Although it was hypothesized that two major factors explaining banking problems were quality of management and honesty of employees, such factors were somewhat reflected in the financials of the banks. Thus, using financial ratios as independent variables would also include these factors to some extent.

Ten financial variables selected for the study were:

1) Liquidity: Cash + US Treasury Securities to Assets
2) Loan Volume: Loans / Assets
3) Loan Quality: Provision for Loan Losses / Opex
4) Capital Adequacy: Loans / Capital + Reserves
5) Efficiency: Opex / Operating Income
6) Sources of Revenue: Loan Revenue / Total Revenue
7) Sources of Revenue: US Treasury Securities / Total Revenue
8) Sources of Revenue: State and Local Obligations' Revenue / Total Revenue
9) Uses of Revenue: Interest Paid on Deposits / Total Revenue
10) Uses of Revenue: Other Expenses / Total Revenue

Six out of these ten variables were significantly different for the two groups for all the four years of analysis from the univariate tests. The number of significant variables increased, as problem bank status approached, for six, seven, eight and nine years prior to problem status for each year between 1969 and 1972. The mean group profiles and dispersion matrices were different across years, requiring quadratic discriminant analysis. Four methods were employed to determine the relative importance of each variable, which were (i) conditional deletion selection, (ii) scale-weighted selection (iii) stepwise forward selection and (iv) stepwise backward selection. Although rankings differed among the methods, results for 1969 indicated that loan-revenue, efficiency and other expenses variables appeared to be clearly among the most important ones whereas interest paid on deposits seemed to be the least important. It was concluded that six or seven variables out of ten accounted for most of the discriminatory power.

The chi-square measure developed by Cooley and Lohnes (1971) showed that, although means of the groups were statistically different, the overlap between groups was very large, which was expected to deteriorate the classification success. Results of the quadratic discriminant analysis showed the following results:

	Misclassification Rates	
Year	Reclassified Sample	Lachenbruch Classification
1969	26,82	35,91
1970	27,73	35,00
1971	24,09	31,36
1972	17,93	24,76

Lachenbruch classification is to run the analysis without an observation at a time and reclassify that single observation with the model that derived without it. Although quite encouraging, the misclassification rates were not low enough, as the groups overlapped significantly. At the day of the study, it was not clearly accepted that quadratic discriminant analysis leads to over-fitting in large size samples, which may be the case here as Lachenbruch classification rates was almost 20-30% worse. Also it was shown that the misclassification rates dropped as problem bank status approached, and group overlaps decreased.

Altman and Loris (1976) proposed a financial early warning system for broker dealers in the United States following the introduction of SIPC (Securities Investment Protection Corporation) in 1970 for the purpose of reimbursing the customers of the bankrupt broker dealers to a limited extent. Between 1971 and 1975 118 Broker Dealers has been bankrupt and SIPC paid out an estimated USD 253 million. At the time NASD, National Association of Securities Dealers, the autonomous regulatory body was in charge of continuous surveillance and supervision of the OTC securities market, had a FEWS (Financial Early Warning System) established for the purpose of spotting potential problem firms before failure and initiating rehabilitative or risk reductive action. (Later NASD became FINRA with an extended coverage and regulatory power) The purpose of this study was to report on the development and findings of this FEWS.

The model employed a dataset consisting of forty failed firms and over one hundred healthy firms. A quadratic MDA was employed instead of linear classification function, which is more appropriate to capture the intragroup interaction effects as well as intergroup associations when dispersion matrices are not equal. The original sample of firms consisted of forty broker dealers who have had a trustee appointed by SIPC during 1971-1973. Although the authors mentioned that it would be better if they could have selected a single year, since the underlying structure and environment of broker dealers were changing over time. However, for the sake of sufficient data, a three year period was chosen. Firm data for the sample was from 1970-1972 annual reports, the year chosen for each firm depending on the date prior to liquidation. 125 healthy firms selected randomly were representative of the total population.

Systematic selection techniques were used to evaluate the discriminating power of alternative combinations of variables. A final profile of six variables was selected, which were Net Income / Total Assets, Total Liabilities plus Subordinated Loans / Owner's Equity, Total Assets / Adjusted Net Capital, Ending Capital minus Capital Additions / Beginning Capital, Scaled Age and Composite. The Composite was a single variable composed of ten separate elements with values of zero or one and was formed by a number of qualities selected by the NASD personnel based on their judgment of indicators. The composite index was the simple addition of these ten scores. Prior probabilities were the same as the ratio of such in the selected sample. Authors suggested changing the cut-off score to account for the misclassification costs can be made by judgment. Lachenbruch hold out method was employed to check the reliability and impressive level of predictive accuracy was observed.

Overall accuracy was 86,2%. An additional surveillance firm sample from year 1973 was also used to test the model. Eight out of twelve failed firms were classified correctly, whereas four undetected firms were classified to be in the medium risk zone. Another run of the model was conducted with quarterly data, for the purpose of having more frequent observations. However net income after taxes / total assets ratio and two components of the composite variable was dropped due to lack of data. Type I error was reported as 12,5% (versus 10.0 of the original model) and Type II error was reported as 15,0% (versus 9.7% of the original model).

Moyer (1977) re-examined Altman (1968) study with more recent data and paid attention to the critics of Joy and Tollefson (1975) study and stated that *ex-ante* validation of Altman (1968) study was not present and this clouds the results driven. 27 pairs of bankrupt and non-bankrupt firms from 1965 to 1975 period were collected. Then the Z-Score model derived by Altman (1968) was used to discriminate the fifty-four new firms which had asset sizes ranging from $15 million to $1 billion where the largest asset size in the sample used by the Altman (1968) study was reported as $25.9 million.

The accuracy of the original model was 75% with 39% misclassification of failed companies and 12% misclassification of non-failed companies. Only three of the twelve misclassified firms were in the "gray zone." Results indicated that the original Altman model parameters were sensitive to either time span or size or both. Then the Altman model was re-estimated by using a stepwise method for the five variables and a direct method that included all of the five variables directly. Results showed that Altman's model contained some superfluous variables. With the data one year prior to bankruptcy, direct model with five variables provided 88,1% predictive accuracy, on the other hand the stepwise model with three variables provided 90,48% predictive accuracy.

Both direct and stepwise models using two years prior to bankruptcy data provided 83,3% accuracy, where the stepwise model only used the same three variables again. For three years prior to bankruptcy, the five variable model had 71,4% accuracy and the stepwise model, which this time included two variables, had 73,8% accuracy. The same two variables were neglected by the stepwise model for all three years, where another one was neglected in the last model. The neglected two variables seemed to add nothing or worse, decrease the accuracy. The original Altman model reported an accuracy of 95%, 72% and 48% for one to three years prior to bankruptcy and it was stated that the model was accurate for two years prior to bankruptcy. It was also shown that accuracy was still acceptable for the third year as well, although it was underlined that further *ex ante* validation tests should be performed to confirm this point.

Next, a comparison with a naive alternative was presented by constructing a two variable MDA based on Beaver's (1968) finding that the cash flow to debt ratios were the best single predictor of bankruptcy and Lev's (1971) use of the balance sheet decomposition measure (BSDM). The same dataset was used to estimate the model and the result was compared to Altman (1968). BSDM was defined as:

$$BDSM_n = \sum_{i=1}^{2}\sum_{j=1}^{2} q_{ij} \log \frac{q_{ij}}{p_{ij}}$$

Where

q_{11} = Current assets in year n / $(TA_n)^2$; q21= Long term assets in year n / $(TA_n)^2$; p_{11}, p_{12} ,p_{21}, p_{22} correspond to similar subscripted q but relate to year n-1.

The overall success rate of the model for the sample with one to three years prior to failure was 85,2%, 83,3%, and 64,81% respectively. Altman's model standed up very well with respect to this alternative multivariate model that incorporated the findings of two widely known univariate approaches, However the alternative model seemed to have significantly fewer misclassifications of failed companies whereas the Altman model performed better in classifying the non-failed companies.

Altman and Eisenbeis (1978), in the form of a reply to the critic of Joy and Tollefson (1975), stated that a better method for the variable importance measure proposed by Altman (1968) may be the conditional deletion method, which yields to the following ranking of variables in terms of importance:

1) Sales / Total Assets
2) Market Value of Equity / Book Value of Total Debt
3) Retained Earnings / Total Assets
4) Working Capital / Total Assets
5) Earnings before interest and taxes / Total Assets,

Such ranking was quite different from the one originally proposed by Altman (1968). Also it was stated that assessing the importance of variables depends heavily on the criterion of importance being employed. Other than this, most of the critics laid out by Joy and Tollefson (1975) were duly addressed, and the model offered by Altman (1968) was supported. Everett and Dunn (1991) and Polit (1996) provided details, use and interpretation of Wilks' Lambda, which is the mostly used statistics as an appropriate method for identifying comparative importance of variables in discriminant analysis.

Olson (1980) employed a conditional logit model to evaluate the probabilistic estimates of firm failure. The dataset consisted of 2058 non-bankrupt firms and 105 bankrupt firms from 1970-1976. Olson also considered the time of release of the financial statements and controlled whether the firm entered the bankruptcy before or after the release date of the financial statements. His findings reported larger error rates than that of the previous studies; however he suggested that embedding some independent variables encountering market price data may reveal better results.

Logit model was used in order to avoid the shortcomings of the Multivariate Discriminant Analysis employed by the previous studies, such as the statistical requirements imposed on the distribution of the predictors. The first three models used the following independent variables, with the following initial sign predictions:

1) log(total assets/GNP price-level index)
2) Total liabilities to total assets (+)
3) Working Capital to total assets (-)
4) Current liabilities to current assets (+)
5) One if total liabilities exceeds total assets, zero otherwise (?)
6) Net Income to total assets (-)
7) Funds provided by operations to total assets (-)
8) One if net income was negative for the last two years, zero otherwise (+)
9) Change in net income from last year to total of current and last year's net income (-)

Three models predicted bankruptcy within one year, two year and within one or two years. All signs of the variables were as predicted initially with the exception of ratio 5, which was positive in the profile analysis. Results of the logit model showed that goodness of fit ratios were 84%, 80% and 72% respectively for the one year, two year and one or two year prior to bankruptcy models. The results indicated that four ratios were statistically significant which are Ratio 1, Ratio 2, Ratio 6 and/or Ratio 7, and Ratio 3 or Ratio 3 and Ratio 4 jointly. In search for additional independent variables, he also tried the funds from operations to sales ratio and a ratio of assets with little or no cash value which came out to be insignificant in a re-run of the first model with the addition of these ratios. Logit allowed the use of different cutoff points to account for the misclassification costs. Although the results were not directly comparable to previous studies, they were significantly more robust. Using the same dataset, MDA was run and predictive power was somewhat worse than previously reported. He suggested additional predictive variables such as ones encountering for market data may improve the results. He also concluded that the predictive power of linear transforms of a vector of ratios seem to be robust across large sample estimation procedures.

Subhash Sharma & Vıjay Mahajan (1980) employed MDA to predict business failures using a pair wise approach. A 46 firm sample was formed by selecting a non-failed firm for each bankruptcy filed firm with similar size and business description. Reliability and the predictive power of the model were satisfactory. Although perfect pairing was not possible and pairing method runs the risk of sample selection bias, this provided a sample with equal number of elements in groups, which overcame the potential problems in running MDA with unequal group sizes. Financial ratios, defined as objective performance indicators by the authors, successfully provided a satisfactory predictive power.

Zmijewski (1984) examined conceptually and empirically two estimation biases which can result when financial distress models are estimated on non random samples. First one was the over sampling of distressed firms (choice based sample biases) and the second one was the "complete data" sample selection criterion (sample selection biases), which is eliminating the observations with incomplete data where financially distressed firms may have higher probability of having incomplete data then healthy firms. He analyzed 17 prior papers and showed that the more the sample departed from population distribution, the greater the rate of the errors reported in these studies. He used a large sample from American and New York Stock Exchanges for the years 1972 to 1978 where number of firms in the population ranged from 2,082 to 2,241 per year. Financial distress is defined as filing a petition for bankruptcy and 81 out of 129 firms bankrupt firms satisfied the complete data criterion. Bankruptcy frequency rates in the population range from 0,49% to 0,94%.

Three appropriate techniques were identified to deal with choice based simple bias, weighted exogenous sample likelihood (WESML), conditional maximum likelihood (CEML) and full information concentrated likelihood (FICML). Among which, WESML is selected for its computational practicality. WESML probit assessment weighs the log-likelihood function by the ratio of the population frequency rate to sample frequency rate of the individual groups. Weighted the log likelihood function adjusts the parameters for the choice based sample. Studies using sample selection probabilities close to population probabilities did not suffer from this bias. However studies using 50% sample frequency rate suffered from over classification of bankrupt firms. In order to demonstrate the bias, the author pooled the data of eighty-one bankrupt firms with complete data and also the data of 1600 non-bankrupt firms. Next, the probit model was run with and without WESML weighting for the samples and with increasing non-bankrupt firm numbers. Six sub data sets starting from 40:40 and gradually increasing to 40: 800 bankrupt to non-bankrupt companies were formed. Results indicated existence of a choice based sample bias and a reduction of such bias in un-weighted probit assessment as results improved while frequency rate was getting closer to population frequency. Also employing probit with WESML technique shows that such bias can also be eliminated to a considerable extent where sample frequency distribution is different from population.

Prediction tests confirmed this bias and showed higher error rates in the samples and methods where bias was present. Again, error rates were decreasing as sample frequency converges to population size or applying WESML. Finally a goodness of fit test was employed and similar results were demonstrated again through construction of seven portfolios with each having six bankrupt (the last one with five) firms and comparing the actual portfolio frequency to the predicted frequency. However, in general the bias does not affect the statistical inferences or the overall classification rates.

The complete data criterion or the sample selection bias, was examined empirically by comparing a bivariate probit assessment, which incorporates the impact of missing data on estimates of bankruptcy probabilities, with a simple probit assessment. The model was estimated on three sub samples: bankrupt firms with complete data, non-bankrupt firms with complete data and firms with incomplete data. Although it was shown that high bankruptcy probabilities were associated with low complete data probabilities, overall classification rates were similar across techniques. Only the probability estimates appear to be affected by the bivariate probit assessment which provides few additional insights.

The adjusted techniques used to estimate the probability distributions fit the probability distribution better and improve the individual group error rates significantly.

Tam and Kiang (1992) tried to identify the potentials and limitations of neural nets as a tool to perform discriminant analysis for its robustness, predictive accuracy, adaptability and explanatory capability using bank default data in Texas. They compared five techniques, which can be viewed in two groups. Machine learning group consisted of neural nets and decision tree (ID3) and statistical technique group consisted of discriminant analysis (DA), logit analysis and k nearest neighbor (kNN). Their data set was formed from the banks that failed in the period from 1985 to 1987. The sample consisted of bank data with one year and two years prior to failure. A failed bank is matched with a successful one in terms of asset size, number of branches, age and charter status. Fifty-nine appropriate pairs were identified, with nineteen financial ratios describing each bank.

The variables included both the ones used in the previous studies and also the ones from CAMEL criteria (Capital, Asset, Management, Equity and Liquidity) used by FDIC (Federal Deposit Insurance Corporation). Management criterion was not included as it is difficult to quantify. Kolmogorov-Smirnov test revealed that only one of the variables had normal distribution. Even after natural logarithm transformation, normality did not improve (thirteen of nineteen still non-normally distributed) so original ratios were used for the rest of the analysis. DA, logistic regression, kNN (only for k=1 and k=3, even numbers of k were not included due to the possibility of a tie), ID3 and neural networks analysis were applied. Evidence showed that non-failed banks have a multi modal distribution which was particularly apparent in one year period and caused the DA models to be insensitive to changes in misclassification costs above twenty-five times. (Misclassifying costs of failed banks as non-failed banks are twenty-five times the opposite). Two neural network architectures were specified; first one did not have an hidden layer and composed of only two neurons (net0) whereas second one had three hidden layers and ten hidden neurons (net10).

The original back propagation algorithm was modified to include prior probabilities and misclassification costs. There was a discrepancy reported in the neural network results which stemmed from limiting the iteration number to 2000, as the iteration halted in a local optimum. Increasing the number of iterations eliminated such discrepancy. In the one year before default model, the methods were ranked in terms of lower misclassification rates to higher and lower type I error to higher as: net10, logit, ID3, net0, DA, K1NN and K3NN. For the two year before default model such ranking was: DA, net10, ID3, net0, logit K1NN and K3NN. In terms of predictive accuracy, which was computed through employing hold out samples, models were ranked as net10, net0, DA, K3NN, ID3 and K1NN. However, the ratios of type one and type two errors were not consistent in the predictive test and two year before default model results were better than one year before default model results, although the initial expectation was otherwise.

One of the causes of such could be that the holdout sample was not representative of the population. In order to overcome this problem, jackknife method that Lachenbruch (1967) proposed was used. This time net10 showed the lowest misclassification cases both in one year and two year before default models. A net with no hidden layers (net0) showed similar performance to DA. However net10 with incorporated hidden layers significantly outperformed DA. Unlike logit, all analysis but ID3 suffered from conveying information about relative importance of individual variables.

Neural nets allow adaptive adjustments to the predictive model as new examples are available, which is an attractive property when the underlying group distributions are changing. It was also proposed that neural networks could be expected to perform better when a multi modal distribution exists. Allowing for adaptive model adjustment and not requiring normal distribution or equal dispersion of independent variables are other important virtues of neural nets. One of the drawbacks of neural nets is the problem of choosing the number of hidden layers, where large numbers of hidden layers can cause over fitting when the number of observations is limited. Another drawback is that the relative importance of individual variables cannot be assessed.

Dimson and Marsh (1995) analyzed the capital requirements for securities firms in a multi country setting and argued on the underlying methodology of the calculation of capital requirements. Their work compared the three methodologies used by the European Union, the United Kingdom and the United States. Actual books of trading companies in the United Kingdom was used, and the capital requirements calculated by the three approaches were compared with the actual volatility of the books. Basically, the methods were then compared through seeking a relation between the changes in the capital required by each approach and the actual volatility of the books. They found that the most effective one was the simplified portfolio approach of the United Kingdom, showing better performance over building block and comprehensive approaches of the United States and the European Union.

Back, Laitinen, Sere and van Wezel (1996) selected thirty-one ratios from the literature and thirty-seven matched pairs of companies from Finland to analyze the default prediction with discriminant analysis, logit analysis and neural networks. Besides comparison of the models, they also introduced different ratio selection procedures for the analysis methods. They used classical stepwise ratio selection for discriminant and logit, and proposed an original ratio selection method for neural networks and genetic algorithms. Below is the ratios selected for liquidity:

1) Cash/Current Liabilities
2) Cash Flow/Current Liabilities

3) Cash Flow/Total Assets
4) Cash Flow/Total Debt
5) Cash/Net Sales
6) Cash/Total Assets
7) Current Assets/Current Liabilities
8) Current Assets/Net Sales
9) Current Assets/Total Assets
10) Current Liabilities/Equity
11) Inventory/Net Sales
12) Net Quick Assets/Inventory
13) EBIT/Total Interest Payments
14) Quick Assets/Current Liabilities
15) Quick Assets/Net Sales
16) Quick Assets/Total Assets
17) Working Capital/Net sales
18) Working Capital/Equity
19) Working Capital/Total Assets

Solidity ratios were:

1) Equity/Fixed Assets
2) Equity/Net Sales
3) Long Term Debt/Equity
4) MV of Equity/Book Value of Debt
5) Total Debt/Equity
6) Total Debt/Total Assets

And Profitability ratios were:

1) Net Income/Total Assets
2) Net Sales/Total Assets
3) Operating Income/Total Assets
4) Rate of Return to Common Stock
5) Retained Earnings/Total Assets

6) Return on Stock

The variables selected for all three models were quite different, where logit analysis picked the fewest and neural networks the largest number of variables. Ratios were separately detected for one year, two years, and three years prior to failure. Except for one, all variables chosen by the logit model is a subset of variables chosen by the discriminant model. The large differences between the variables picked by three models are explained by (i) the real and significant different characteristics in different firms that can be measured by different financial ratios, where alternative empirical methods use this information in alternative ways and (ii) random selection of methods among the variables with high correlations when large number of ratios are picked.

Then the ratios are divided into three subgroups of liquidity, solidity and profitability. The dominant measure for all one and three years prior to failure was liquidity, where for two years prior to failure it was solidity for discriminant, profitability for logit and liquidity again for neural networks. The reason behind dominance of liquidity was attributed to the bankruptcy code of Finland, where most of the defaults were due to liquidity deficiencies, as companies may navigate through other requirements but not liquidity. Further, some of the liquidity measures also account for profitability or solidity, as a clear cut distinction is not always possible.

Factor analysis revealed seven factors, where discriminant model and genetic models included variables from four out seven of these factors, whereas logit was sufficed with two. In the logit model there are fewer variables and dimensions than the other two models. Below is the table of results for the three models.

	Type I Error			Type II Error			Total Error		
Year	DA	Logit	NN	DA	Logit	NN	DA	Logit	NN
1	13.51%	13.51%	5.26%	16.22%	13.51%	0%	14.86%	3.51%	2.70%
2	24.32%	27.03%	26.32%	18.92%	29.73%	27.78%	21.62%	28.40%	27.03%
3	16.22%	16.22%	5.26%	37.84%	35.14%	27.78%	27.03%	25.70%	16.22%

In the one and three years prior to default models, neural network model was the best performer, and discriminant analysis was the best performer for the two years prior to default model. Logit posted the highest error in all years prior to default.

The study of Back, Laitinen, Sere and van Wezel (1996) introduced a new variable selection technique; neural network model was outperformed by discriminant in two years prior to failure, which is a rare reporting in the literature. Most probably this was the result of the variable selection technique, where logit and discriminant analysis used solidity and profitability ratios for the two years prior to failure model, but neural network model was limited to information from liquidity only. Logit used the minimum number of variables and posted the worst results. Perhaps a combination of variable selection techniques may have a chance to provide better results.

Yıldıran (1998) examined financial intermediaries in Turkey and after comprehensively defining the financial distress in financial intermediaries, proposed that financial ratios can be used to classify the financial intermediaries as successful and unsuccessful. Yıldıran argued that simply taking the financial intermediaries that are bankrupt not only creates a statistically small number of unsuccessful firms, but also is not the most appropriate way to follow in creating a statistically sound model. The main purpose of the study was to pave the way for an early warning system that may have practical use. Such a model may be used to predict the financial distress early enough to provide the regulatory authorities with sufficient time to act and prevent or minimize the potential damage that may be caused by the default of the financial institution.

Within this context, the financially distressed companies are defined as (i) financial intermediaries who had their licenses revoked by CMB (Capital Markets Board of Turkey) and a lawsuit for bankruptcy has been filed and (ii) financial intermediaries whose licenses are revoked temporarily for more than two months or more than once due to weak financial structure. It was also underlined that the license revoking action by CMB does not take place only for weak financial position but also for other administrative compliance reasons. Special attention was paid in identifying the financially distressed firms and ones whose licenses were revoked for the reasons that were not related to financial distress were not included. Although CMB permanently ceased the operations of fourteen financial intermediary institutions in the period of analysis, financial statements of only six of those were available due to several reasons.

In identifying the independent variables, it was assumed that, in line with the relevant literature, change in general economic conditions are not expected to have a discriminating power among firms, since whole industry is affected in the same way. The management and personnel were specified as the main factors that distinguish the successful and unsuccessful companies, which are very difficult to observe and measure directly. However, the managements and personnel’s performance will be reflected in the financial statements and success of the firms, which can be objectively measured. Consequently, financial ratios were used as independent variables in the study.

The risks the financial intermediaries face in their daily operations were extensively defined. By definition, financial intermediary institutions are just the middleman between the capital markets and the investors and do not inherently carry any financial risk. They duly execute the orders of their customers, provide safekeeping services for the securities and charge a commission for the services rendered. However, in case their customers do not meet their obligations, i.e. not deliver the securities they previously ordered to sell or the cash for the clearance of their orders, the intermediary institution is liable for the counterparties of the transactions. In this setting, default of many customers may create substantial burden on the financial intermediary.

The second type of risk may arise from the margin trading and short-selling transactions. Financial intermediaries are allowed to provide loans to their customers from their own resources or through borrowing from banks. Both short sale and margin trading activities are risky transactions and can quickly lead to the default of the customer of the intermediary institution. The risk level and required collateral shall be closely monitored by the intermediary institution. However, competition and large volume of transactions may also lead to large losses.

The third type of risk identified may stem from improper safekeeping of assets, i.e. deposit customer assets as collateral and borrowing loans that will eventually be used for the trading of the shareholders or managers of the firm or the firm itself. Fourth type of risk may arise when the commission income of the firm is not sufficient to cover the operational costs. Fifth, in case of IPOs, intermediary institutions underwrite the portion or whole of the offering, and in case shares are not sold at the pre-committed price levels, then the firm may post large losses and may become insolvent. Sixth, the agencies of the intermediary institutions, which are contracted third parties operating at other locations may create risk, as the operations of the agencies cannot be perfectly controlled and the intermediary institutions are fully responsible for all of the liabilities of their agencies. And finally, financial intermediaries may use their portfolio management operations to collect deposit. Such funds may not be managed according to proper portfolio management principles set out by CMB and may be used for speculative purposes which in turn may hurt the financial standing of the firm.

For the purposes of the study, financial statements of firms from 1993, 1994 and 1995/6 were collected. Interim financials for 1995 were selected on purpose, as the six unsuccessful firms, whose financials were available, defaulted in the first months of 1996 and year-end financials were not available. Twenty-four financial ratios selected through literature survey, expert opinions and availability of information due to Turkish accounting standards are presented below:

1) Current Assets / Total Assets
2) Net Income / Shareholder's Equity
3) Shareholder's Equity / Total Assets
4) Total Debt / Shareholder's Equity
5) Current Assets / Total Debt
6) Operating Income / Gross Sales
7) Current Assets / Current Liabilities
8) Accounts Receivable / (Shareholder's Equity – Tangible Fixed Assets – Intangible Fixed Assets)
9) Operating Expenses / Gross Sales
10) (Tangible Fixed Assets + Intangible Fixed Assets) / Shareholder's Equity
11) Operating Income / Shareholder's Equity
12) Current Liabilities / Shareholder's Equity
13) (Current Assets – Current Liabilities) / Shareholder's Equity

14) (EBIT + Interest Expense) / (Shareholder's Equity +Total Debt)
15) Net Income / Current Assets
16) Long Term Liabilities / Shareholder's Equity
17) Total Liabilities / Total Assets
18) Current Liabilities / Total Assets
19) Account Receivable / Current Liabilities
20) Net Income / Total Assets
21) Net Working Capital / Total Assets
22) (Shareholder's Equity – Total Liabilities) / Total Liabilities
23) Total Liabilities / (Shareholder's Equity – Fixed Assets)
24) Operating Expenses / (Shareholder's Equity – Fixed Assets)

Although trend variables (change in the variable through one of two year periods) are significant in the literature, such were excluded due to lack of data. As interim financials were used for 1995, they were not perfectly comparable with year-end figures. Only 1993 and 1994 data may yield trend variables for only one single year, which did not seem to be enough to construct trend variables. Therefore, trend variables were excluded, although it was noted that they were shown to be significant in the literature.

Normal distribution of the independent variables was examined by Chi Square, Kolmogorov – Smirnov and Shapiro – Wilks tests. Although most of the raw variables did not show normal distribution for all of the analysis years, logarithm or square roots transformations did.

The statistical techniques that were utilized in the literature for default prediction, which were multiple regression, discriminant analysis and logit and probit models, were compared. Among those, discriminant analysis technique was selected due to its proven robust results and efficiency in the literature, although such technique was criticized for the strict pre requisite assumptions of multivariate normality and equivalence of covariance matrices among groups. Despite such flaws, discriminant analysis is also proven to post satisfactory predictive power in the literature. Financial analysis contemplated from five parts:

1) 1995/6 figures were used to construct a linear discriminant function for the purpose of determining the success of the independent variables in classifying the successful and unsuccessful firms. The model classified 91,7% of the unsuccessful firms and 85,6% of the successful firms correctly. Although the dataset suffers partially from unavailability of data (i.e. detailed books, trend variables etc.) such results, especially the 91,7% correct classification of unsuccessful firms, where incorrect classification costs are much higher, was satisfactory.

2) 1995/6 figures were used to construct a linear discriminant function with forward stepwise method in order to identify the independent variables that are significant. Independent variables 2,3,6,10,11,13,14,19,20,23 and 24 were determined to be significant and overall correct classification ratio was 86,27%. Such variables are then used for 1993 and 1994. As expected, the prediction power decreased, although slightly, as years to default increased. Correct classification figures for 1994 and 1993 were 84% and 83% respectively.

3) In third part, a quadratic discriminant model was constructed with the 11 significant variables specified in the previous part. Quadratic model yielded perfect classification results, 100%, for 1995/5, 91,35% for 1994 and 100% for 1993. It is clearly shown that financial ratios were in fact very useful in constructing an early warning system through quadratic discriminant function. Prior probabilities for the model was set as 0,5 and need not be revised due to almost perfect classification rates. In this part of the study, the predictive power of the model was robust and useful in practical applications.

4) In fourth part, linear discriminant model was constructed to determine significant independent variables for each of the years and test whether using different independent variables for each period improves the predictive power. Variables 6, 8,11,12,19 and 22 were significant for 1994 and variables 1, 10,11,14,15 and 19 for 1993. Predictive power of the linear models with the above mentioned variables for each year were 88, 46% and 89% for 1994 and 1993 respectively. Predictive power of the linear model was improved with this method, which was an expected result.

5) In the fifth part, effects of prior probabilities in the predictive power of the models were examined. Using 11 independent variables, 9 models for each year with prior probabilities ranging from 0,1 to 0,9 with 0,1 steps were constructed for each year. It was shown that the cut off score of 0,5 almost provides the optimum

results for every year, and proposed be the one that is appropriate for prediction of firm success.

It was stated that using interim financials created two major difficulties, the first one is the calculation of the tax on the interim profits and the second one is the inability to use trend variables. However, interim financials was the only solution to expand the unsuccessful firm sample to a level that is enough to construct a sound model. Furthermore, although the assumptions of the discriminant analysis were not satisfied, the predictive power of the models constructed, especially quadratic discriminant analysis, was quite satisfactory.

The importance and contribution of Yıldıran's study to literature is two folds; firstly, it is the first study in this area conducted for Turkish companies and intermediary institutions. Second, the study proves that financial ratios can be used to construct an early warning system, however much more detailed empirical analysis and better datasets may be required to build a robust model. However, despite the limited data available, the models posted very successful classification rates and may indeed qualify to be used by the practitioners in the industry.

Shumway (2001) proposed a Simple Hazard Model for more accurate prediction of bankruptcy. He criticized previous static models like logit for having an inherent selection bias. That is, by choosing to observe each firm's characteristics arbitrarily, forecasters who use static models introduce an unnecessary selection bias. 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, whereas other firms fail in their first year.

By employing hazard model, he also found out that most of the independent variables used in static models were insignificant, which were market size, past stock returns, idiosyncratic standard deviation of stock returns, ratio of net income to total assets and total liabilities to total assets.

Shumway's sample consisted of 3182 US firms and 39745 firm years, where 300 bankruptcies were present. To avoid outliers, independent variables were truncated to 99% and 1% of original values where applicable. However, results with truncated and untruncated variables did not differ significantly. Also, for missing accounting data, the value from the past year(s) was filled in. By doing so, number of bankruptcies observed increased by almost 10%. Previous models dropped such data, which in this study was proposed to be one of the reasons for inflating significance of some independent variables. He compared hazard model with the models used by the studies of Altman (1968) and Zmijewski (1984). Hazard model significantly outperformed Altman's model, whereas not Zmijewski's. Main reason for reporting similar results with Zmijewski was argued as that the only two statistically significant predictors were highly correlated, thus with only one variable, both his and Zmijewski's models suffered to post good results. Next, market based independent variables together with accounting based independent variables as stated above were employed and 95% of the bankrupt firms were reported as above the probability mean, showing that market based variables significantly improved the predictive power.

Reynolds, Fowles, Gander, Kunaporntham and Ratanakomut (2002) used probit and logistic binomial regression analysis to predict the financial companies that survived the crisis of 1997 and past using the data for the period 1993-1996. Further, they were also able to estimate the probability of a firm surviving and operating in 1998 through employing a multinomial ordinal logistic model. The data set contained ninety-one companies, out of which, thirty-five survived to 1997 and a final bunch of twenty-three out of 1997 survivors, to 1998. They used a technique that allowed predicting probability of failure rather than just failure. The predictive power of the logit model they employed, however, showed less reliability (68%) than figures reported by some recent similar papers.

Altman (2005) introduced a scoring system (EMS) for emerging corporate bonds based on the original Z-Score model developed by Altman (1968). It was decided to modify the well tested and applied Z-Score model that was developed for the manufacturing companies as there was enough data to develop a scoring system from scratch for the emerging market corporations. Since its development in 1968, the Z-Score model has evolved in the past 35 years and now it can be applied to non-manufacturing, industrial firms and to private and public entities. The Z-Score model for the emerging markets was then proposed as:

$$\boxed{\begin{aligned} Z = 6{,}56\,\frac{Working\ Capital}{Total\ Assets} + 3{,}26\,\frac{Retained\ Earnings}{Total\ Assets} + 6{,}72\,\frac{Operating\ Income}{Total\ Assets} \\ + 1{,}05\,\frac{Book\ Value\ of\ Equity}{Total\ Liabilities} + 3{,}25 \end{aligned}}$$

The constant term (3,25) derived from the median Z-Score for bankrupt US entities enabled to standardize the analysis so that a default equivalent rating is consistent with a score below zero. Major accounting differences between emerging market countries and

US were also taken into account during the computation of the ratios. The Z score was also calibrated against the credit ratings of 750 manufacturing and non-manufacturing US companies. Thus the Z-Score was then able to match The United States Bond rating equivalent for a given emerging company.

In the next step the adjusted bond rating for foreign currency devaluation vulnerability was taken into account. Vulnerability was assessed based on the relationship between non-local currency revenues minus costs compared to non-local currency interest expense, and non local currency revenues versus non local currency debt. If the vulnerability of the company was high, then the rating from the Z-Score based matching was downgraded a full rating class i.e. from BB+ to B+, if the vulnerability was neutral, only one notch (BB+ to BB) and unchanged for low vulnerability.

In the third step, the rating is adjusted for industry safety rating equivalent, and for up to each full letter grade difference, bond rating equivalent was adjusted down or up a notch. In the fourth step, based on the analyst views, rating is adjusted depending on the competitive power and dominance of the company in the market. In fifth, the rating was adjusted for the special debt issue features like a collateral or high quality guarantor. In the final step, the difference between the sovereign bond yields and US treasuries were added to the corresponding yield of the rating found in the previous step.

Then, the same procedure was repeated by plugging in market value of equity instead of book value of equity in the proposed emerging market Z-Score model. If the difference from the first analyses was one notch than the rating was unchanged, if it was two notches, then a one notch update was made and if the difference was more than three notches (one full rating class) or more, the adjustment was two notches. The reason for this last adjustment was the concerns about the inefficiencies of the emerging market stock markets, so the market value of equity was not embedded in the model directly, but in relation with the book value of the equity.

The model was than tested with the Mexican data, for the period following the currency crisis in 1994. The model was accurate enough, as downgraded companies also received a subsequent degrading by S&P and Moody's or file bankruptcy or the D rated companies missed interest payments subsequently. Thirteen Mexican corporations had agency ratings (Moody's or S&P or other) and comparing these to the EMS model rating also yielded close results. EMS assigned higher ratings to the top companies, as it was not bounded by the sovereign risk rating. The study shows a successful application of the Z-Score model for a non-US data, although it was suggested that country specific models shall be developed, if possible.

Brockett, Golden, Jang and Yang (2006) tried to identify troubled insurers rather than failed ones in order to have a better application in real life. Such approach was expected to provide the regulators with the opportunity to take necessary actions further prior to failure. The criteria for financially troubled firms were set as receiving a hazardous financial condition notice or more severe regulatory action. The research was conducted to predict such action through an early warning system. A three year data was used among the life insurance companies. MDA, Logit and Neural Networks methods were employed and predictive power of all were also assessed. Two types of Neural Networks methods were employed, namely back propagation and LVQ. Both neural net models showed lower error rates than MDA and Logit. Increasing the misclassification costs further improved the neural net results over MDA and Logit.

Five different data sets were used and the predictive power of the data sets with respect to each neural net method was also assessed. Neural net models proved to outperform traditional statistical methods and were concluded to be promising in financial early warning signaling. Performance of the neural nets were robust over time and a significant intervention and rehabilitation time may be provided to regulators in order to identify problems earlier and take necessary actions to prevent failure.

Uğurlu and Aksoy (2006) used twenty-seven failed and twenty-seven successful manufacturing companies form Istanbul Stock Exchange from 1996 to 2003 period in order to identify the predictors of corporate financial distress and create models using discriminant analysis and logit analysis. The dataset was formed by finding twenty-seven size wise pairs for the twenty-seven failed companies. Although where thirty-two firms were in financial distress during the analysis period, five of them were eliminated due to missing data.

Logit analysis revealed eleven predictors whereas discriminant analysis revealed ten. Six of the predictors identified by the both models were: EBITDA / Total Assets, EBIT / Sales, fixed asset turnover, return on equity, size and tax burden. Firm size showed an unexpected positive relation with financial distress, which indicates that larger firms tends to have higher leverage and more of the financially distressed firms were larger.

Default was defined as the disqualification from ISE listing due to Article 16 of listing regulation or Article 324 of Turkish Commercial Law, which basically require delisting of companies that has negative equity or miss its debt obligations. Size wise selection of the sample was made by grouping the companies according to their market capitalizations for the year 1999, which was a year of high economic activity prior to the deep financial crisis of 2001. All twenty-two failed companies were in the lowest quartile in terms of market capitalization, and the matching twenty-two successful firms were selected randomly from the same quartile. There were no significant difference in group sizes at 95% confidence level.

Financial statements were adjusted for inflation, setting the base year as 1996. A total of eighty financial ratios were developed in the first stage, grouped into eight categories including profitability, liquidity, and solvency, degree of economic distress, leverage, efficiency, variability and size. Factor analysis was conducted to identify the variables that seem to be doing the best job in predicting financial distress and extracted twenty-two variables. For any distressed firm, data of the previous year end was used, so the lead time differed for the firms from three months to nine months. The predictive accuracy of discriminant model was 85,9% and that of the logit model was 95,6% (97,5% non-failed versus 91.4% failed). Although, testing with holdout sample was not possible due to limited sample size, other reliability tests were satisfactory.

Not all of the variables had the expected signs, although there was a logical theoretical explanation reflecting dynamics of the marketwise characteristics which show the distortions in the corporate financial structures revealing the impact of the constraints of the financial system surrounding the corporations. Accuracy of logistic regression decreased, as years to default increased, which was the very expected result. Even at the fourth year prior to failure, overall predictive accuracy was 87,1%. In all of the four years, logistic regression posted better results than discriminant analysis.

Aminian, Suarez, Aminian and Walz (2006) compared the accuracy of Neural Networks with standard linear OLS regression. Both industrial production and GDP growth of The United States were used to compare the two methods. Economic data, usually analyzed with linear approaches, was chosen on purpose. Quarterly GDP data from 1966 to 2004 and monthly Industrial production data from 1953 to 2004 were used in the study. Five input variables for GDP and six for Industrial Production were chosen. In the process of training the neural networks, five out of 147 GDP data points were left out for testing, whereas twenty out of 601 were left out in the case of Industrial Production data. Test data were selected randomly in order to avoid any bias that may be caused by a non-random region of inputs. Procedure was run for 3000 times for both GDP and Industrial production to overcome regional data input bias. Then a coefficient of determination was introduced to compare OLS and neural net results. In case of GDP, neural networks posted a 39% improvement due to inclusion of non linear effects, whereas in the case of industrial production the improvement was 73%.

Ozkan-Gunay and Ozkan (2007) tried to predict the failure of Turkish banks during the 1999 to 2001 period through using financial ratios for the period 1990-2001. They employed artificial neural network method with a back propagation approach and GDLR to classify the banks. The sample consisted of fifty-nine banks, twenty-three out of which failed between 1999 and 2001. At a confidence level of 90%, 76% of the failed banks were correctly classified, whereas an accuracy better than 90% for the non-failed banks were reported. Their results showed that failed banks could be predicted years before failure, which may provide the authorities significant time to rehabilitate.

CHAPTER 3

DATA

Intermediary Institutions

104 financial intermediation companies are incorporated in Turkey and regulated by the Capital Markets Board (CMB), which is an autonomous body. The list of the bank owned and non-bank owned financial intermediaries and the types of operating licenses each hold are provided in APPENDIX A: INTERMEDIARY INSTITUTIONS IN TURKEY

Fundamental purpose of Intermediary Institutions in Turkey is to facilitate the transactions in the Istanbul Stock Exchange (ISE) and Turkish Derivative Exchange (TURKDEX) between buyers and sellers of bonds, stocks and derivative contracts. In order to serve for this purpose, Intermediary institutions also carry out activities like providing loans to their clients, facilitating short sales, consultancy services or portfolio management. Intermediary institutions also intermediate partially or wholly underwritten IPOs and SPOs. Depending on the number of operations an Intermediary Institution undertakes, a different type of license is required, which are provided by CMB. Each Intermediary Institution is required to have a minimum paid-in capital, amount of which depends on the types of licenses held.

Intermediary institutions execute the buy-sell orders of their customers, and charge a certain commission over the amount of transaction. Securities held by the customer of an intermediary institution are the property of the customer, not the intermediary institution. All securities are registered at the ISE Settlement and Custody Bank under the name of the customer of the intermediary institution. At the end of every day, balances are settled and monitored by CMB. Current system of operations prevents an intermediary institution to cause large damages to the system in case of default, as the securities of the clients are not at risk as they are owned and registered as their property.

However, intermediary institutions provide loans to their customers which are funded by the equity capital or bank loans raised by the intermediary institution. Customer loans are secured by the underlying securities that are bought by such loans. CMB sets the loan limit that an intermediary institution can extend, based on the equity capital and the type of collateralization. Further, intermediary institutions invest their own cash in the financial instruments and leverage their own transactions as well. CMB makes sure that the equity capital is enough to cover the exposure of the intermediary institutions at all times. Another type of risk that may be borne by an intermediary institution may stem from underwriting an IPO or SPO, which is also under the supervision of CMB.

Provided that there is not a fraud, if an intermediary institution defaults, the largest loss shall be limited to the equity capital of the intermediary institution and none of the other stakeholders, i.e. clients or creditors, face monetary loss. Each exposure is matched by a collateral or equity capital of the intermediary institution. A decent corporation may step into gray areas in bad times in order to survive or save the day, and such gray areas may get darker and darker to the line of fraud. For example, the use of clients' securities to cover the losses in the intermediary institutions' portfolio to steer the company through a market crash may worsen the damage to the system. In order to prevent such actions and limit any default to the equity capital, CMB shall act in a timely fashion to interfere with the operations. Intermediary institutions are regulated in a way to minimize their risk of default, by limiting the exposure proportional to the equity capital.

Capital Adequacy Reports

Regulation of financial standing of Intermediary Institutions is organized by the CMB Communiqué on Principles Regarding Capital and Capital Adequacy of Brokerage Houses, Series 5, No: 34 published in 1998. Financial standing of each company is monitored through Capital Adequacy Reports ("CARs"), filed weekly by each intermediary institution. Contents of the report includes a detailed trial balance sheet and information on buying and selling volumes of each type of securities and calculations towards the capital requirements of CMB. The content of the CARs are tailored for the operating environment of the intermediary institution industry and enables much more efficient and detailed information than regular financial statements.

CMB showed the courtesy to allow for the use of the CARs for the purposes of this study. As every intermediary institution is required the file these reports, the dataset covers the whole industry, and no sampling is required, eliminating the choice based sample biases or sample selection biases by design which were almost inevitable in previous studies as put out by Zmijewski (1984)

In addition to above, availability of such data set shall allow this study to overcome some of the shortfalls of the previous works that were criticized. Financial statements were usually made available couple of months following the relevant period and sometimes the companies are bankrupt even before the financial statements for the previous period are available. Furthermore, CARs are required to be timely filed and delays lead to application of sanctions by CMB.

Intermediary institutions, by the nature of their business, are operating in a very dynamic environment, where the conditions can rapidly change. It might be the case that an intermediary institution may expose itself to a great amount of position risk without being truly noticed between two regular financial statement periods of three months. Having frequent data is expected to contribute a great extent to the accuracy, reliability and predictive power of this study.

Last but not the least, customized nature of this reports for the purpose of monitoring this specific industry also allows access to details that is otherwise impossible through regular financial statements. However, there are some drawbacks as well. Figures like total sales or net income was not present in the CARs, as such figures could not be calculated at the weekly frequency required by the CMB due to the specific operating characteristics of the industry.

Capital Requirements

CMB has four capital requirements for Intermediary Institutions:

A. Minimum Paid-in capital

Any Intermediary Institution shall have a minimum equity between TL 195k and TL 502k depending on the type of CMB license it holds in 2009. These amounts are updated regularly in order to preserve the real value against inflation and also follow developments in the markets.

B. Own Funds Requirement

Capital Adequacy Base or “Own Funds” shall not be less than any each of the

a) Minimum paid-up capital

b) Total Risk Provisions

c) Last 3 months’ operating expenses

C. Global Indebtedness Limit

Sum of all indebtedness including financial and non-financial, current and non-current shall not exceed 15 times of the Own Funds

D. Liquidity Requirement

a) Net Current Assets shall exceed Current Liabilities

b) Net Current Assets does not include the assets with 100% risk weighting and items that are deducted from equity for the purposes of Own Funds calculations

Companies that do not comply with these regulations are given a remedy period and if they cannot comply within this period, operations of the intermediary institution are suspended and licenses are revoked. For the purposes of Capital Requirements, Capital Adequacy Base (“CAB”) or “Own Funds” is defined as:

Shareholder’s Equity less:

(i) Fixed Assets

(ii) Tangible Fixed Assets

(iii) Intangible Fixed Assets

(iv) Fixed asset investments, left after deducting their capital commitments and provision for decrease of value of fixed asset investments, excluding the ones traded in stock exchanges and other organized markets

(v) Other Fixed Assets

(vi) Receivables from Related Parties

Receivables from Related Parties subject to deduction are defines as uncollateralized receivables from personnel, partners, subsidiaries, affiliated undertakings, individuals and institutions who have direct or indirect relations in terms of capital, management and auditing, even with the title of customer and capital market instruments not traded in stock exchanges and other organized markets issued by such individuals and institutions

Most of the breaches of capital requirements stem from the second requirement, which is the requirement that CAB shall not be less than any of the minimum paid-in capital, total risk provisions and last three months' operating expenses. Minimum paid-in capital is set by the CMB depending on the type of license the intermediary institution holds, and is updated regularly. Last three months operating expense is also straightforward. And finally, the calculation of risk provisions contemplates from the addition of the following four items:

A. Position Risk
   - (i) 10% of the current value of stocks and bonds that are traded in the exchanges, 100% of the value for the ones that are out of exchanges
   - (ii) 1%-5% for government bonds
   - (iii) 5% of the value of precious metals, 10% of the value of commodities that are the underlying for derivative contracts, 100% of the value of other commodities
   - (iv) 1%-8% of the value of accounts receivables
   - (v) 10% of the value of long term receivables and financial fixed assets

(vi) 3% of the value of short term payables, 5% of the value of long term payables

B. Counter Party Risk

(i) 5% of the value of uncollateralized receivables from local banks, insurance companies, investment funds and investment grade foreign institutions.

(ii) None for foreign Central Banks and exchange institutions

(iii) 100% of the value of the ones that are not mentioned

(iv) Receivables also include the ones that are borne from intermediation of short sale of capital market instruments.

(v) Only liquid financial instruments are accepted as collateral, provided that direct recourse is on demand and with simple legal procedures.

C. Concentration Risk

If the value of any one of the financial instruments held or receivable from any party is between the below stated ranges of the Own funds, the position risk is multiplied by:

(i) 40%-60%: 3 times

(ii) 60%-80%: 4 times

(iii) 80%-100%: 5 times

(iv) 100%-250%: 6 times

(v) >250%: 9 times

D. FX Risk

(i) Foreign currency denominated net long and short positions are calculated without any maturity considerations, and the larger one is selected as the FX exposure

(ii) If the FX exposure exceeds 2% of the Own Funds, 8% of the excess is calculated as FX risk

Almost all of the breaches of capital requirements stem from excess total risk provisions. If a company that barely meets the capital requirements loses money in one period, it shall lower its position risk the next period or receives a warning from CMB to top up its capital within a certain period depending on whether it's the first, second or third time in the last year. The intermediary institution is also provided with the opportunity to provide a bank guarantee for the deficit in order to extend this remedy period.

In case Own funds of an intermediary institution falls below these requirements, CMB applies the following measures:

(i) If own funds are at 75% or more of the required amount, a remedy period of 30 working days shall be granted to the brokerage house in case of occurrence for the first time within that year and 20 working days for the second.

(ii) If own funds are between 40% and 75% of the required amount, a remedy period of 20 working days shall be granted in case of occurrence for the first time and 10 days for the second.

(iii) If own funds are less than 40% of the required amount, a remedy period of 10 working days shall be granted to the intermediary institution.

Within this remedy period, if the brokerage houses fail to increase their Own Funds to the required level, their activities are suspended temporarily or their licenses are cancelled partially or completely. If deficiencies occur more than the specified times in a calendar year, no remedy periods are granted.

The Dependent Variable

Instead of defining default as bankruptcy, the default for the purposes of this study is defined as the breach of capital requirements set out by CMB. A similar definition in the literature was also used by Brockett, Golden, Jang and Yang (2006). The intermediary institutions are already very closely monitored by CMB and their operations are well defined, thus it is almost impossible for a company to go bankrupt without breaching the capital requirement criterion first. Although a company may fail due to fraud without any breach of CMB regulations, prediction and detection of fraud is beyond the scope of this study.

As CARs are designed specifically to monitor the intermediary institutions in their well-defined operating environment, capital requirements can be regarded as the true measure of financial stability of an intermediary institution. A breach is a sign of loss of financial stability, which is a pre-default event. The occurrence of breach leads to regulatory actions and may result in bankruptcy, liquidation or suspension of CMB licenses. Thus, in a way current regulations are designed to detect loss of financial stability prior to bankruptcy.

By definition, predicting a pre-default event is expected to be much harder than predicting default. However, CARs tailored nature for the industry and frequency of data may help to overcome this difficulty.

Although current monitoring efforts and regulations are doing an excellent job in preventing loss of financial stability, as organizations adapt to the current regulations and innovations in the market to improve profits or forces of competition may push the players in the industry to find ways to take risk and create return. In order to keep up with the ever increasing complexity of the capital markets, regulations shall be one step ahead. This study may aid in establishing another layer of early detection to serve this goal.

The Data

CMB collected CARs from every one of the intermediary institutions since the beginning of 1999, and data from a total of 247 time points were available.

Table 1: Frequency of Data

Period	Frequency	Number of Data Points
1.1.1999 - 31.7.2000	Monthly	19
31.7.2000 – 15.9.2008	Bi-weekly	196
15.9.2008 – 31.5.2009	Weekly	32

Most of the decrease in the average number of companies reporting each period is mostly attributable to the consolidation in the industry through mergers and acquisitions or liquidation of small companies out of competition. The names and identities of the companies were not revealed by CMB for confidentiality reasons, and the details of reasons to stop reporting of a particular company is not disclosed as well. However, the information that a company which is not reporting to CMB is clearly not operating as an intermediary institution, and is a sufficient information for the purposes of this study. This confidential nature of the dataset is respected through not conducting any research to get additional data, i.e. match the data provided by CMB with the ISE listed intermediary institutions. Actually, no further research was truly necessary, as CARs contain very detailed information on the companies and each company can be truly assessed unanimously. However, inclusion of market price data may improve results if the identities of the institutions are available to the researcher.

Table 2: Number of companies throughout the analysis period

Period	Average Number of Companies
1.1.1999 – 31.12.2003	117
31.12.2003 – 31.12.2006	101
31.12.2006 – 31.5.2009	94

More than 25,000 reports filed in almost 10, 5 years.

The data consists of 247 MS Excel Files, each having entries for a number of companies ranging from 78 to 133. Each excel file has four sheets, where the first one contains the trial balance sheet contemplating of approximately 125 items. The first sheet also includes the mark to market values of these 125 items and also the calculations of the Position Risk, Counterparty Risk, FX Risk and Concentration Risk. The second sheet has the calculation of capital adequacy base and tests its sufficiency. The third sheet shows the calculation of the liquidity requirements and the fourth sheet provides basic trading information, buying and selling volumes of stocks, bonds etc.

Construction of the Database

Independent variables used in the literature to detect bankruptcy or financial distress are pooled. Not all of them were possible to construct from the CAR database, as figures from income statement like net income, total sales or operating income was not available, which is the disadvantage attached to the high frequency of data. Most probably, income statement could not be reported on a weekly basis due to the requirement of the calculation of rather complicated items like depreciation. Specific operating characteristics of the industry may be another reason for the lack of some of the income statement data.

Lack of some of the income statement data leads to the elimination of some of the critical ratios which are among the significant predictors of bankruptcy, like the asset turnover ratio or return on equity or assets. Although important for manufacturing companies, some of the unavailable ratios are already not very relevant for intermediary institutions industry, like asset turnover. Some of them are inferred from the available data, like inferring Net Income from change in Capital Adequacy base or Shareholders Equity or Total Sales from total buying and selling volume.

In addition to the financial predictors extracted from the literature, additional variables are also constructed from the CAR database in order take advantage of the details of the tailored database reflecting the specific characteristics of the industry. A final set of thirty-six financial variables were constructed and grouped under six headings:

A. Asset Structure

(i) LTL / SHE : Long Term Liabilities to Shareholders Equity

(ii) SHE / TA : Shareholders Equity to Total Assets

(iii) SHE – TL / TL : Shareholders Equity less Total Liabilities to Total Liabilities

(iv) FA / SHE : Fixed Assets to Shareholders Equity

(v) TL / SHE – FA : Total Liabilities to Shareholders Equity less Fixed Assets

(vi) TL / CAB : Total Liabilities to Capital Adequacy Base

(vii) TL / TA : Total Liabilities to Total Assets

(viii) CAB / TA : Capital Adequacy Base to Total Assets

(ix) CA / SHE : Current Assets to Shareholders Equity

(x) NWC / TA : Net Working Capital to Total Assets

(xi) NWC / SHE : Net Working Capital to Shareholders Equity

(xii) CL / SHE : Current Liabilities to Shareholders Equity

(xiii) AR / SHE – FA : Accounts Receivable to Shareholders Equity less Fixed Assets

B. Risk Type

(i) CPR to TRP : Counterparty Risk Provision to Total Risk Provision

(ii) CPR to CAB : Counterparty Risk to Capital Adequacy Base

(iii) PR to TRP : Position Risk Provision to Total Risk Provision

(iv) PR to CAB : Position Risk to Capital Adequacy Base

(v) TRP to CAB : Total Risk Provision to Capital Adequacy Base

(vi) Δ TRP : Six months average change in Total Risk Provision

C. Liquidity

(i) AR to CL : Accounts Receivable to Current Liabilities

(ii) CA to CL : Current Assets to Current Liabilities

(iii) CA to TA : Current Assets to Total Assets

(iv) CA to TL : Current Assets to Total Liabilities

D. Operation

(i)	Δ CAB to TA	: Six months average change in Capital Adequacy Base to Total Assets
(ii)	Δ SHE to TA	: Six months average change in Shareholders Equity to Total Assets
(iii)	OP to CAB	: Last 3 months Operating Expenses to Capital Adequacy Base
(iv)	Δ (CAB – TRP) to TA – (SHE – CAB) :	6 months average change in the difference of Capital Adequacy Base and Total Risk Provision to Total Assets less the difference of Shareholders Equity to Capital Adequacy Base
(v)	TRP + OP to CAB	:Total Risk Provision plus Last 3 months Operating Expense to Capital Adequacy Base
(vi)	OP to CAB – TRP	: Last 3 months Operating Expense to the difference of Capital Adequacy Base to Total Risk Provision

E. Market Power

(i)	VS	: Volume Share, total volume of securities handled by the intermediary institution to the gross total volume handled by all of the intermediary institutions

(ii)	Δ VS	: 6 months average change in Volume Share
(iii)	V to CA	: Volume of securities handled to Current Assets
(iv)	V to SHE-FA	: Volume of securities handled to Shareholders Equity less Fixed Assets
(v)	V to CAB	: Volume of securities handled to Capital Adequacy Base
(vi)	Δ V	: Percentage change in the volume of securities handled

F. Other

(i)	Prev Def	: Whether the intermediary institution defaulted prior to the date of the observation or not

Following the definition, a 247 X 180 matrix is formed pooling the entire capital adequacy excess or deficit figures for all of the filings and all of the companies across all periods. All deficiencies are marked and below is the histogram for the number of periods a deficiency or no data is reported in the following ten periods following a deficiency.

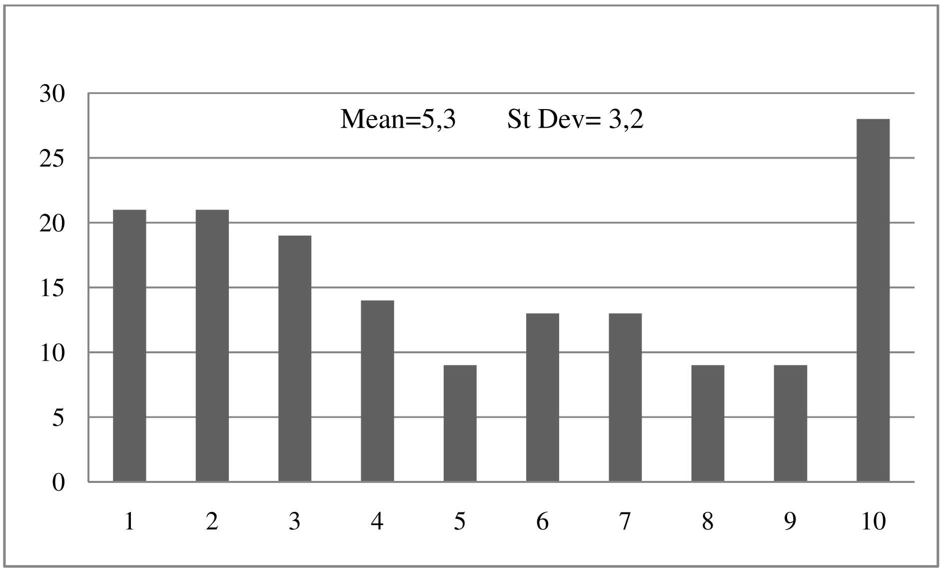


Figure 5: Histogram of deficiencies in the next ten periods

A total of 156 defaults in capital requirements were present in the dataset. Below is the time wise distribution of these data points:

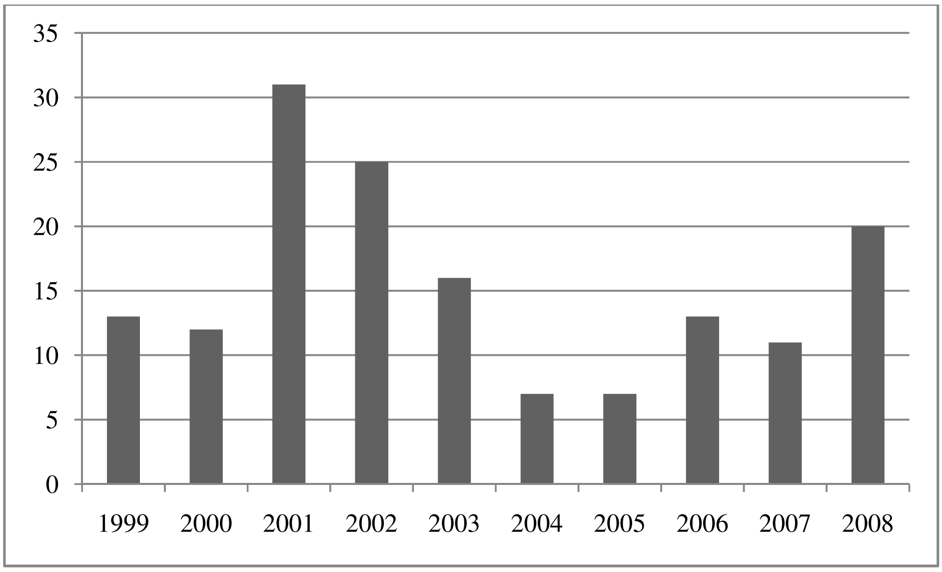


Figure 6: Number of default points

Number of defaulters increase in the times of economic downturn, as it is apparent in the increases in 2001 and 2008.

After all of the default points are marked, data for the thirty-six variables are pooled in separate matrices for each data point for three months prior to the deficiency. Ratios are calculated for all data points and means of the three months are calculated. For each data point, two to twelve values are averaged, depending on the frequency and completeness of data. Averaging helps in the dampening of outliers, although as Shumway (2001) presented, eliminating outliers did not have significant effects on the results. Also averaging adds a time component, where the data three months prior to default is also accounted for in the average, and for practical implications, signaling will be smooth, i.e. a company will drift from non-defaulters to defaulters instead of jumping.

Next, default points which misses one thirds or more of the previous periods' data for any of the thirty-six ratios are eliminated. Due to missing data, nineteen default points are lost and final dataset comprised from 136 default data points.

Non-default data points are formed in a similar way, with the following criteria:

(i) No default has occurred during the past three months and the upcoming six months

(ii) No missing data during the last three months

(iii) Each data point is unique, i.e. if a value is included in the average of a data point it is not included in the average of another.

This led to 2876 non-default data points for each of the thirty-six ratios. Below is the table for the time wise distribution of these data points

Table 3: Default Percentages throughout the Analysis Period

Year	Defaulters	Non-Defaulters	% defaulters
1999	6	192	3,0%
2000	12	336	3,4%
2001	31	274	10,2%
2002	22	288	7,1%
2003	14	255	5,2%
2004	7	313	2,2%
2005	6	305	1,9%
2006	10	278	3,5%
2007	10	272	3,5%
2008	17	252	6,3%
2009[1]	1	111	0,9%
Total	136	2876	4,5%

Total number of data points is close to an even distribution, however number of defaulters increase right after financial crises.

Change in variables with respect to previous six months are calculated through taking differences between the period of calculation and six months prior to that period of calculation and repeating this operation for the three month averaging period. Then the ratios calculated and averaged.

Following is the table for the means, standard deviations and the p value of the t-test for the significance differences of the variables with respect to defaulter group and non-defaulter group.

[1] 2009 data is for the first five months

Table 4: Descriptive Statistics of Groups

Ratio	Defaults		Non-Defaults		Total		
	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation	Sig.
LTL to SHE	,0919	,1523	,0635	,0647	,2521	,2558	,199
OP to CAB	,4755	,3175	,2577	,2675	,1973	,1841	,000
OP to CAB-TRP	1,6066	5,9105	,4202	,4738	1,8026	1,3034	,000
AR to CL	1,1831	1,2744	1,7929	1,7654	3,7289	3,8039	,062
AR to SHE-FA	1,2984	1,3549	,9688	,9837	6,1558	6,2925	,542
CA to CL	4,5825	8,0311	6,5008	6,4142	23,4732	23,9554	,352
CA to SHE	1,5372	1,1928	1,3053	1,3158	,9150	,8986	,004
CA to TA	,6795	,1693	,7168	,7151	,1844	,1849	,021
CA to TD	5,0879	13,3083	5,1600	5,1568	15,4706	15,5674	,958
CA-CL to SHE	,5038	,2824	,6234	,6180	,3377	,3392	,000
CL to SHE	1,0334	1,1983	,6819	,6978	,8577	,8351	,000
CAB to TA	-,0212	,1508	,0559	,0524	,7657	,7828	,251
FA to SHE	,2731	,1952	,2173	,2198	,1907	,1901	,001
CPR to TRP	,1712	,2161	,1166	,1191	,3935	,3998	,114
CPR to CAB	,0561	,1231	,0291	,0303	,0897	,0877	,001
NWC to TA	,3114	,2121	,4161	,4114	,2239	,2234	,000
SHE to TA	-,0083	,1772	,0470	,0445	1,9648	2,0103	,749
PR to TRP	,7282	,2519	,7879	,7852	,4166	,4226	,102
PR to CAB	,1519	,1234	,1122	,0950	,1140	,0968	,000
TRP to CAB	,2469	,2413	,1628	,1451	,1666	,1517	,000
TRP+OP to CAB	,7224	,4341	,4205	,2647	,4341	,2816	,000
SHE-TL to TL	3,5500	8,7300	4,4852	17,4004	4,4429	17,1042	,533
SHE to TA	,5865	,2059	,6688	,1979	,6651	,1989	,000
CAB-TRP to TA-(SHE-CAB)	-,0286	,1574	,0503	1,0955	,0467	1,0711	,401
TL to SHE-FA	1,4106	1,5915	,7847	11,5944	,8130	11,3353	,529
TL to CAB	1,3322	1,4810	,8853	1,0263	,9055	1,0548	,000
TL to TA	,3780	,2146	,3125	,2078	,3155	,2085	,000
VSc	2,8899	16,5595	10,6125	77,1408	10,2638	75,4771	,244
V to CA	68,6144	114,3949	59,6248	115,5875	60,0307	115,5302	,375
V to SHE-FA	128,2366	157,1631	89,8119	165,0355	91,5469	164,8563	,008
V to CAB	116,3097	138,2032	84,0707	133,9005	85,5264	134,2412	,006
VS	,0038	,0074	,0093	,0255	,0091	,0250	,012
Vc	14,7691	124,6697	17,0910	111,3870	16,9861	111,9989	,813
CAB to TA	,4437	,1906	,5372	,2058	,5330	,2060	,000
TRPc	1,4497	1,6047	2,0348	11,9382	2,0084	11,6711	,568
PrevDef	-,3824	,9274	,2851	,9587	,2550	,9671	,000

Distribution of each variable is checked and none of them were normally distributed. Square root transformation, logarithmic transformation and inverse transformation of each variable is checked and only a few variables showed normal distribution. Results of the Kolmogorov-Smirnov and Shapiro-Wilk tests are provided in APPENDIX B : TESTS OF NORMALITY. Consequently, it is decided to use the original values of the variables

CHAPTER 4

METHODOLOGY

Multivariate Discriminant Analysis (MDA), Logit, Probit, Hazard Models and more recently Neural Networks were employed to predict bankruptcy in the literature. Early studies like Altman (1968) employed MDA and reported satisfactory reliability and predictive power. Later in the 1980s, MDA was criticized for requiring normal distribution, linearity and lack of having a time component and logit model was proposed as a better alternative by Olson (1980). Zmijewski (1984) proposed a modification to the algorithm of logit in order to account for the bias that may be caused by the flaws of the method and also for decreasing the effects of sample selection bias that is inherent in the financial distress prediction studies. Logit models were proposed as a better alternative and it was shown that in some cases logit and hazard models, which are a special case of logit, provides better estimates.

Shumway (2001) employed a "simple hazard model" and heavily criticized MDA and standard logit models for lacking the time component and showed that most of the independent variables used by the previous studies were actually insignificant due to the biases introduced.

As computing power increased geometrically in the past decade, machine learning systems like neural networks became feasible to apply. Among many, Tam and Kiang (1992), Brockett, Golden, Jang and Yang (2006) and Ozkan-Gunay and Ozkan (2007) employed neural networks to predict financial distress. Neural networks are favored over the statistical techniques, i.e. MDA or logit, mostly for not needing the data to be normally distributed and allowing non-linearity.

One of the drawbacks of neural networks is that the results do not explain the relative importance of the independent variables, which limits the explanatory findings. Also neural networks are prone to over fitting of data where special attention needs to be paid to determination of the hidden layers.

Tam and Kiang (1992) compared most of the available methods and concluded that neural networks outperformed other methods consistently. However, although MDA is heavily criticized for its drawbacks, it still delivers competitive prediction rates compared to neural networks and logit. This study is intended to employ Neural Networks as it is recently the most favored prediction method, however the classic method, MDA will not be ruled out as well.

Although the dataset fails the normality tests, it is shown in the previous studies that, MDA can provide fairly good results in holdout samples. MDA has the advantage of good explanatory power of the importance of the independent variables and may come handy in detecting which independent variables are more useful over the others. On the other hand, neural nets have shown to have better predictive power and almost no statistical requirements on the independent variables. However, neural nets are like a black box and it is very difficult to judge the importance of the independent variables and choose the ones with better explanatory power. Both methods will be utilized for comparison and the findings of the methods will be used to complement each other.

Discriminant Analysis

Discriminant Analysis has statistical requirements of the parameters, which are very similar to those of the regression. Actually, discriminant analysis is very similar to regression, where almost identical results can be achieved by both methods. Below are the assumptions and compatibility of the dataset:

Table 5: Evaluation of Basic Assumptions of Discriminant Analysis for the Dataset

➢ Cases should be independent	➢ Cases can be regarded as independent
➢ Predictor variables must have a multi-normal distribution	➢ None of the predictor variables has multi-normal distribution even after: o eliminating outliers o log transformation o 1/x transformation o square root transformation
➢ Within group variance-covariance matrices should be equal across groups	➢ Variance-Covariance matrices are not equal and Box's M statistics is significant.
➢ Group membership should be mutually exclusive and collectively exhaustive	➢ This assumption is valid by the definition of the dataset
➢ The predictors are not highly correlated with each other, correlation between two predictors is constant across groups and means and variances of predictors are not correlated	➢ Although some of the predictors are highly correlated, across groups values are mostly non-uniform

Two important assumptions of the discriminant analysis are violated; the first one is the unequal variance-covariance matrices, which will be shown in the upcoming analysis results. The second one is that none of the variables have normal distribution, and none of the data transformation techniques resolve this issue.

Quadratic Discriminant Analysis, which accounts for the unequal variance-covariance matrices is a proposed solution in the literature. However it is not recommended for groups with large differences in membership, which is the natural case for this study. Equal groups can be drawn from the dataset to address this issue, however this introduces other biases as put out by Zmijewski (1984).

Discriminant Analysis Model 1

A discriminant analysis is run with all thirty-six variables entering together for exploratory purposes. Within group variance-covariance matrices are used which lead to linear discriminant function with the assumptions that variance-covariance matrices are equal. Below are the basic statistics of the first run:

Table 6: Test of Equality of Covariance Matrices for the Discriminant Analysis Model 1

Log Determinants

DEPENDENT	Rank	Log Determinant
DEFAULT	34	-41,923
NON-DEFAULT	34	-10,994
Pooled within-groups	34	-9,555

Test Results

Box's M		8509,317
F	Approx.	13,03
	df1	595
	df2	166237,377
	Sig.	0,000

Two variables, CL to SHE and TRP + OP to CAB fail the tolerance test and analysis is run with 34 variables. Although Box's M statistics is known to come out significant when variance covariance matrices are equal but group sizes are large, log determinants of the two groups also show that, variance-covariance matrices are quite different. This result is also confirmed with visual inspection of the means and standard deviations of both groups, which is provided in APPENDIX C: GROUP STATISTICS.

There are also significant correlations between some of the independent variables, which is another violation of the assumptions of discriminant analysis. Correlation matrix and covariance matrices are shown in APPENDIX D : COVARIANCE AND CORRELATION MATRICES.

Table 7: Summary Of Canonical Discriminant Functions for Discriminant Analysis Model 1

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	,105[a]	100	100	0,309

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	0,905	299,544	34	0,000

Canonical correlation of discriminant scores with the dependent variables is 0,309, which is not promising. However, Wilks' Lambda shows that the model classified the observations better than chance significantly. Below are the classification results of the initial model:

Table 8: Classification Results for Discriminant Analysis Model 1

		DEP	DEF	NON-DEF	Total
Original	Count	DEF	97	39	136
		NON-DEF	547	2329	2876
	%	DEF	71,3	28,7	100
		NON-DEF	19	81	100
Cross-validated	Count	DEF	89	47	136
		NON-DEF	558	2318	2876
	%	DEF	65,4	34,6	100
		NON-DEF	19,4	80,6	100

Cross validated results are calculated by leaving-one-out classification, which gives signs of over fitting. This might be due to high correlations among independent variables as shown in the APPENDIX D : COVARIANCE AND CORRELATION MATRICES. Despite all flaws of multicollinearity, non normality and unequal variance-covariance matrices, initial result are not bad, almost 80% overall correct classification rate is achieved.

Discriminant Analysis Model 2

In order to make up for the defects of the first model, the number of predictor variables decreased through taking in the ones that actually help the classification and leaving out the ones that do not. As it is shown in Table 4, not all of the variables are significantly discriminating between two groups. Discriminant Analysis with stepwise entry of variables (F to enter 3,84 and remove 2,71) is run. Within group covariance matrices is used for the function again and 9 variables enter the discriminate analysis:

Table 9: Stepwise Entry / Removal Statistics for Discriminant Analysis Model 2

		Wilks' Lambda							
						Exact F			
Step	Entered	Statistic	df1	df2	df3	Statistic	df1	df2	Sig.
1	OPtoCAB	0.947	1	1	3010	167	1	3010	0
2	PrevDef	0.939	2	1	3010	98	2	3009	0
3	OPtoCAB-TRP	0.933	3	1	3010	72.5	3	3008	0
4	CA-CLtoSHE	0.931	4	1	3010	55.9	4	3007	0
5	VS	0.929	5	1	3010	45.9	5	3006	0
6	LTLtoSHE	0.928	6	1	3010	38.9	6	3005	0
7	NWCtoTA	0.924	7	1	3010	35.1	7	3004	0
8	CAtoSHE	0.919	8	1	3010	33.2	8	3003	0
9	TLtoCAB	0.917	9	1	3010	30.1	9	3002	0

Table 10: Test of Equality of Covariance Matrices for the Discriminant Analysis Model 2

Log Determinants		
DEPENDENT	Rank	Log Determinant
DEFAULT	9	-20.270
NON-DEFAULT	9	-22.670
Pooled within-groups	9	-21.733

Test Results		
Box's M		2496.639
F	Approx.	54.176
	df1	45
	df2	178069.971
	Sig.	0.000

This time the difference between log determinants is reduced significantly, although the Box’s M statistic is still significant. Canonical correlation of discriminant scores are slightly reduced to 0,288 from 0,309. Wilks’ Lambda is still significant showing that model is doing better than chance. Below are the classification results:

Table 11: Classification Results for Discriminant Analysis Model 2

		DEP	DEF	NON-DEF	Total
Original	Count	DEF	90	46	136
		NON-DEF	561	2315	2876
	%	DEF	66.2	33.8	100
		NON-DEF	19.5	80.5	100
Cross-validated	Count	DEF	89	47	136
		NON-DEF	565	2311	2876
	%	DEF	65.4	34.6	100
		NON-DEF	19.6	80.4	100

Still the model has almost 80% accuracy, and the difference between original and leave one out classification is reduced, pointing the effects of over fitting are also reduced.

Table 12: Correlations of Independent Variables in Discriminant Analysis Model 2

Correlation	Prev Def	OP to CAB	OP to CAB-TRP	CA-CL to SHE	VS	LTL to SHE	NWC to TA	CA to SHE	TL to CAB
PrevDef	1								
OPtoCAB	-0.207	1							
OPtoCAB-TRP	-0.033	0.245	1						
CA-CLtoSHE	0.014	-0.118	-0.05	1					
VS	0.03	-0.012	0.031	-0.004	1				
LTLtoSHE	-0.041	0.106	0.054	$\boxed{0.659}$	0.048	1			
NWCtoTA	0.117	-0.336	-0.137	$\boxed{0.641}$	-0.028	0.027	1		
CAtoSHE	-0.15	0.18	0.135	0.354	-0.025	0.323	-0.23	1	
TLtoCAB	-0.17	0.376	0.238	0.131	0.032	0.413	-0.441	$\boxed{0.696}$	1

Three correlations marked above are large enough to cause concern, while rest of them seem to be satisfactory. In order to further look into multicollinearity, Standardized Canonical Discriminant Function Coefficients, Structure Matrix and Wilks' Lambda tables are provided below:

Table 13: Standardized Canonical Discriminant Function Coefficients in Discriminant Analysis Model 2

		Structure Matrix		Wilks' Lambda	
CA-CLtoSHE	-1.480	OPtoCAB	0.785	OPtoCAB	0.947
NWCtoTA	0.936	PrevDef	-0.482	PrevDef	0.939
LTLtoSHE	0.839	OPtoCAB-TRP	0.460	OPtoCAB-TRP	0.933
OPtoCAB	0.677	NWCtoTA	-0.325	CA-CLtoSHE	0.931
CAtoSHE	0.591	TLtoCAB	0.294	VS	0.929
PrevDef	-0.335	CA-CLtoSHE	-0.246	LTLtoSHE	0.928
OPtoCAB-TRP	0.270	CAtoSHE	0.176	NWCtoTA	0.924
TLtoCAB	-0.228	VS	-0.153	CAtoSHE	0.919
VS	-0.141	LTLtoSHE	0.078	TLtoCAB	0.917

The differences in the ranking of variables in the Table 13 may be due to multicollinearity, and it seems that high correlations between CA – CL to SHE, LTL to SHE and NWC to TA, and correlation between TL to CAB and CA to SHE are the ones that are most likely causing problem.

Discriminant Analysis Model 3

Among three correlated variables CA-CL to SHE, LTLtoSHE and NWCtoTA of model two, the one with the highest Wilk's Lambda for standalone discriminating power, CA-CLtoSHE is selected to enter and CAtoSHE is selected over TLtoCAB. Dropping three variables to overcome multicollinearity, six variables enter to the third model.

Table 14: Test of Equality of Covariance Matrices for the Discriminant Analysis Model 3

Log Determinants		
DEPENDENT	Rank	Log Determinant
DEFAULT	5	-11.736
NON-DEFAULT	5	-12.597
Pooled within-groups	5	-11.906
Test Results		
Box's M		1965.542
F	Approx.	129.297
	df1	15
	df2	207414.37
	Sig.	0

Gap between log determinants of the groups further decreased, pointing that group variances are now closer; however Box's M is still significant, although this might, to some extent, be attributable to the large sample size. However, visual inspections of the group statistics of the remaining variables are still not comforting.

Table 15: Standardized Canonical Discriminant Function Coefficients in Discriminant Analysis Model 3

		Structure Matrix		Wilks' Lambda	
OPtoCAB	0.678	OPtoCAB	0.853	OPtoCAB	0.947
PrevDef	-0.367	PrevDef	-0.524	PrevDef	0.939
OPtoCAB-TRP	0.318	OPtoCAB-TRP	0.500	OPtoCAB-TRP	0.933
CA-CLtoSHE	-0.166	CA-CLtoSHE	-0.267	CA-CLtoSHE	0.931
VS	-0.158	VS	-0.167	VS	0.929

CA to SHE did not enter this model, although it did in the previous model. As shown in Table 15, ranking of variables in all three Standardized Canonical Discriminant Function Coefficients, Structure Matrix and Wilks' Lambda tables now agree. With almost half the variables of the previous model, canonical correlation only decreased slightly to 0.266 from 0.288.

Table 16: Classification Results for Discriminant Analysis Model 3

		DEP	DEF	NON-DEF	Total
Original	Count	DEF	90	46	136
		NON-DEF	645	2231	2876
	%	DEF	66.2	33.8	100
		NON-DEF	22.4	77.6	100
Cross-validated	Count	DEF	90	46	136
		NON-DEF	646	2230	2876
	%	DEF	66.2	33.8	100
		NON-DEF	22.5	77.5	100

Classification results of the original variables did not change, however leave-one-out classification results are improved. Cross validation and original results are almost identical, which shows that now the model is stable. Original classification results remained the same, although slightly worse than the first model with all 36 variables, 71.3% versus 66.2%. However this is most probably due to over fitting of the original model. Prediction accuracy of non-defaulters, down by almost 5% is noticeable.

Having multicollinearity and over fitting problems solved, and although the log determinants of the groups are now much closer, there is still doubt on the effects of inequality of the variance-covariance matrices. A solution to this problem is quadratic discriminant analysis which is running the analysis with separate variance covariance matrices for groups. However, quadratic discriminant function is not recommended for samples with unequal group sizes.

5- Variable model is run with specifying separate variance-covariance matrices and results are compared. Below is the table for same and separate variance – covariance matrices for different cut off points:

Table 17: Sensitivity of Classification Results for Same and Separate Covariance with respect to cut off points

Same Covariance			Separate Covariance		
Cut-Off	DEF	NON-DEF	Cut-Off	DEF	NON-DEF
0.2	95.60%	41.00%	0.25	100.00%	0.00%
0.25	90.40%	49.40%	0.3	85.30%	57.50%
0.3	86.80%	56.80%	0.35	72.80%	70.40%
0.35	78.70%	63.70%	0.4	66.20%	77.50%
0.4	73.50%	69.20%	0.45	60.30%	82.90%
0.45	72.10%	73.20%	0.5	52.90%	86.00%
0.5	66.20%	77.60%	0.55	44.10%	89.20%
0.55	60.30%	81.70%	0.6	41.20%	90.80%
0.6	56.60%	85.20%	0.65	33.80%	92.70%
0.65	48.50%	88.20%	0.7	29.40%	93.80%

Results show that both models do not dominate each other in terms of prediction of both defaulters and non-defaulters. However, Figure 7 below shows that both models yield very close results for the purposes of this study. Although ranking of observations according to different discriminant scores shows different ranking for the models, below graph shows that, for the purposes of this study, variance-covariance matrix difference among groups shall not be an important concern.

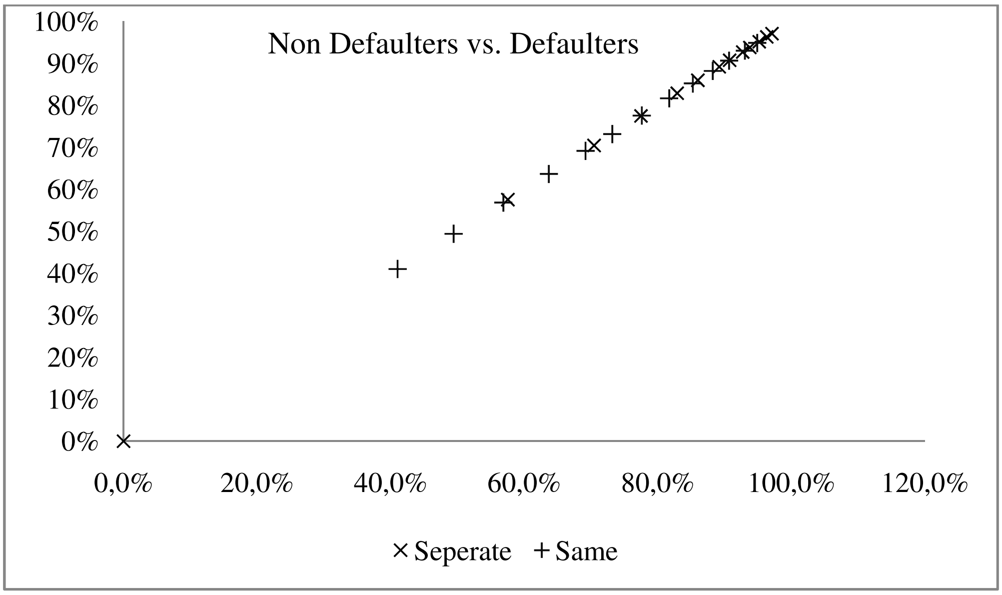


Figure 7: Comparison of accuracy of models using separate and same covariance matrices

The chart presented in Figure 7 is constructed through putting change in defaulters and non-defaulters versus to change in cut-off ratio, as shown in Table 17. Both separate and same variance-covariance matrix models lie on the same line, and it is safe to conclude that using separate variance-covariance matrices does not affect the final results, although the ranking with respect to discriminant scores of observations differ.

<u>Final Discriminant Model with Holdout Test</u>

In order to truly test the reliability of the final model, the data points from 7/2008 to 5/2009 are selected as holdout sample. 5 variables OP to CAB, Prev Def, OP to CAB – TRP, CA – CL t o SHE and VS entered the model, and same variance-covariance matrices for the groups are used.

Table 18: Classification Results for Final Discriminant Model

Cases Selected		DEP	DEF	NON-DEF	TOTAL
Original	Count	DEF	90	38	128
		NON-DEF	652	1975	2627
	%	DEF	70.3	29.7	100.0
		NON-DEF	24.8	75.2	100.0
Cross-validated	Count	DEF	90	38	128
		NON-DEF	652	1975	2627
	%	DEF	70.3	29.7	100.0
		NON-DEF	24.8	75.2	100.0

Holdout		DEP	DEF	NON-DEF	TOTAL
Original	Count	DEF	5	3	8
		NON-DEF	42	207	249
	%	DEF	62.5	37.5	100.0
		NON-DEF	16.9	83.1	100.0

Original sample posted 70.3% correct prediction for defaulters versus 75.2% correct predictions for non-defaulters. Holdout sample, on the other hand, posted 62.5% and 83.1% correct predictions for defaulters and non-defaulters respectively. In order to truly assess and compare the holdout and original model performances, sensitivity of the correct predictions with respect to different cut off scores are presented in Figure 8 and Figure 9.

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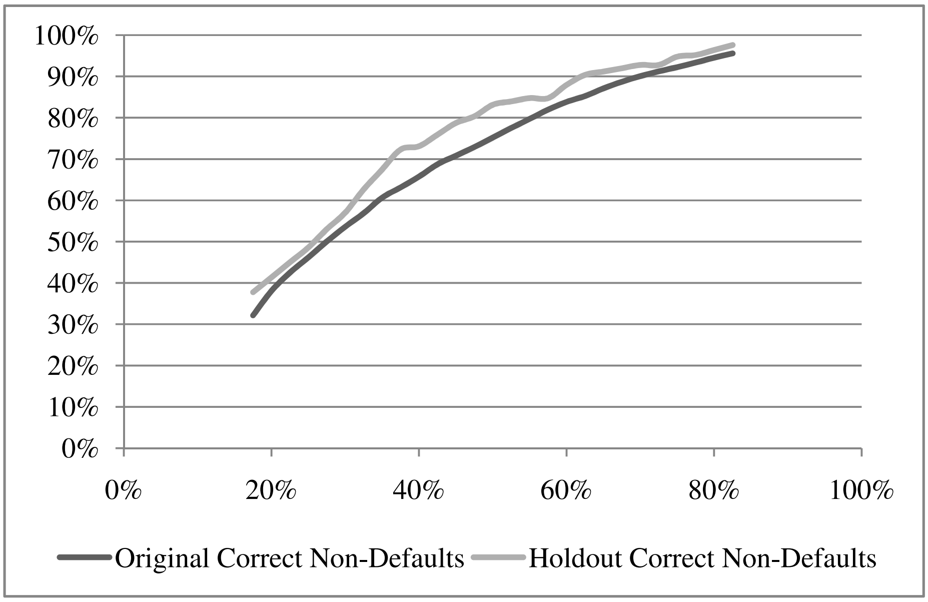

Figure 8: Comparison of final discriminant model performance for non-default group in original and holdout samples

In Figure 8 holdout sample performance is better than original sample performance in terms of correct non- defaulter predictions. However, the case is opposite in terms defaulters as shown in Figure 9.

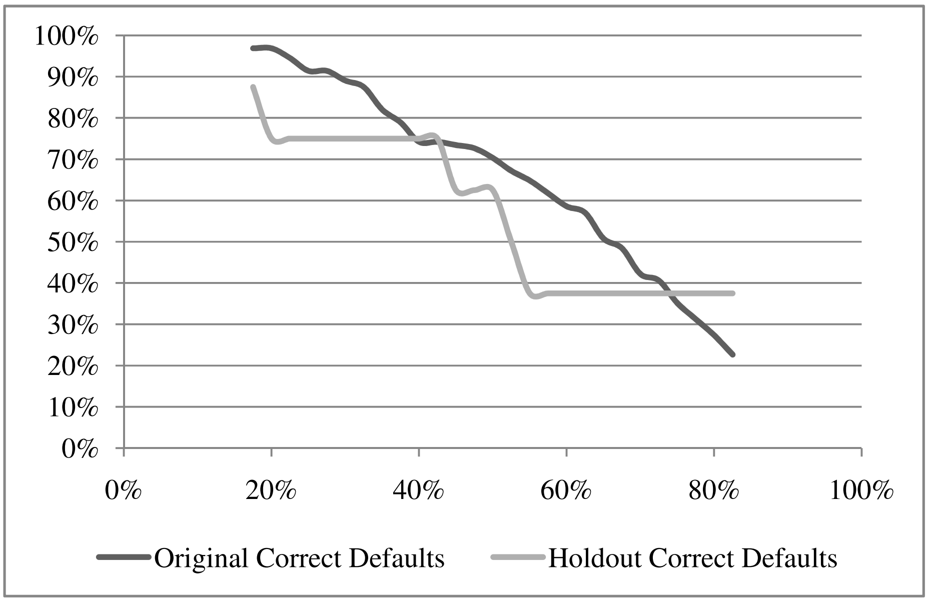

Figure 9: Comparison of final discriminant model performance for default group in original and holdout samples

Overall, holdout performance shows that predictive power of the discriminant model with five variables is satisfactory. Correct default and non-default predictions with respect to cut-off points are presented in APPENDIX E: FINAL DISCRIMINANT MODEL RESULTS for both original and holdout samples.

Discriminant Equation

For the 9 - variable Discriminant Model 2, the discriminant function is:

$$Disc.Score = -0{,}3498\ x\ Prev\ Def + 3{,}5258\ x\ \frac{OP}{CAB} + 0{,}1513\ x\ \frac{OP}{(CAB - TRP)} - 0{,}4394\ x \frac{(CA - CL)}{SHE} - 5{,}6389\ x\ VS + 3{,}3264\ x\ \frac{LTL}{SHE} + 4{,}2000\ x \frac{NWC}{TA} + 0{,}6432\ x \frac{CA}{SHE} - 0{,}2165\ x\ \frac{TL}{CAB} - 0{,}7568$$

The signs of NWC to TA, CA to SHE and TL to CAB were the opposite of the theoretical knowledge, i.e. increasing current assets lead to increased score favoring default. Opposite signs are another sign of over fitting of the 9 variable model due to multicollinearity.

For the 5 - Variable Model without the holdout sample, the discriminant function is:

$$Disc.Score = -0{,}3833\ x\ Prev\ Def + 3{,}5273\ x\ \frac{OP}{CAB} + 0{,}1783\ x\ \frac{OP}{(CAB - TRP)} - 0{,}4935x \frac{(CA - CL)}{SHE} - 6{,}3238\ x\ VS - 0{,}5680$$

All signs are in line with theoretical knowledge in the 5 - Variable Model. The coefficients are also close to that of the model with nine variables, but variable predicted with opposite sign are dropped off.

For the 5-Variable model with the holdout sample, the discriminate function is:

$$\boxed{\begin{aligned} Disc.Score = {} & -0{,}4194\ x\ Prev\ Def + 3{,}6628\ x\ \frac{OP}{CAB} + 0{,}1477\ x\ \frac{OP}{(CAB - TRP)} \\ & - 0{,}5350x\frac{(CA - CL)}{SHE} - 6{,}1503\ x\ VS - 0{,}5687 \end{aligned}}$$

Variable Analysis

OP to CAB: 3 months operating expenses to Capital Adequacy Base

3 months operating expense relates to the efficiency of operations, and capital adequacy base can be regarded as a measure of the size of the net capital managed with such operating expense. Although it might be advocated that total assets may be a better denominator, two companies with equal asset sizes where one investing heavily in government bonds and the other in stocks will need different amounts of capital to support these operations, where the latter will suffice with much less capital. Therefore, Capital Adequacy Base is a better denominator for this purpose. This is the most important ratio which appeared at the top of the structure matrix and in almost every period as shown in Table 23.

Prev Def: Previous Defaults

This is a measure which determines whether an intermediary institution is defaulted since 1999 to the date of the observation. The negative sign predicts that if the company have defaulted in the past, it is more likely to default in the future. Although this measure is not popular in the literature, it comprises valuable information in prediction of capital adequacy deficiency. An intermediary institution which has not defaulted in the past, most probably has the necessary external resources from its shareholders to prevent default when it is approaching or evaluates risk better than others, which in a way shows the competency of the management.

OP to (CAB-TRP): 3 month operating expenses to the difference of Capital Adequacy Base and Total Risk Provision

Although this ratio seems to be close to OP to CAB, it measures a different dimension as its correlation with such ratio for defaulted intermediary institution population and non defaulted intermediary institution population and total population are very low as can be seen in APPENDIX D : COVARIANCE AND CORRELATION MATRICES. Capital Adequacy Base minus Total Risk Provision is the net capital that is free of risk for the intermediary institution. It corresponds to the real reserve held by the company for rainy days and shows the risk aversity of the management. Proportion to 3 months operating expenses scales it with respect to company size.

(CA - CL) to SHE: The difference of Current Assets and Current Liabilities to Shareholders Equity

Current Assets minus Current Liabilities accounts for the cash position of the company. As per the liquidity requirement, current assets shall always exceed current liabilities.

Otherwise CMB will issue a warning and if not corrected within the remedy period, the intermediary institution faces the risk of license suspension. Except a few instances intermediary institutions do not fail from this requirement during the analysis period. Although this ratio was criticized to have lost its information content due to window dressing, frequent reporting seems to prevent this. The amount of cash position is scaled with respect to the shareholders equity, which is a measure of the size of capital under management. Cash position also accounts for the flexibility of the company to adjust to the changes in positions held in the dynamic operating environment of the intermediary institutions.

<u>VS: Percentage of the share of volume of transactions handled</u>

Volume Share accounts for the core business performance of the intermediary institutions, which is to facilitate the transactions between the capital markets and investors. The transactions handled by the intermediary institution are divided by the whole amount of transactions handled in the industry. It is a better measure than total volume of the stock market, as government bond and portfolio transactions were also included. As intermediary institutions charge a commission over the volume of the transactions, it is a measure of core market share, and is an efficient measure of the relative market power of an intermediary institution with respect to rest of the industry.

Neural Networks

Haykin (1994) put out the definition of the neural network as a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects:

- Knowledge is acquired by the network through a learning process
- Interneuron connection strengths known as synaptic weights are used to store the knowledge

McNelis (2005) defined neural networks as a method relating a set of input variables to a set of one or more output variables like the linear and polynomial approximation methods. The difference between a neural network and other approximation methods is that the neural network makes use of one or more hidden layers, in which the input variables are squashed or transformed by a special function, known as a logistic or logsigmoid transformation. While this hidden layer approach may seem esoteric, it represents a very efficient way to model non-linear statistical processes. Neurons process the input data in two ways, first by forming linear combinations of the input data and then by “squashing” these linear combinations through a function like hyperbolic tangent. The inputs are thus transformed by the squashers before transmitting their effects on the output.

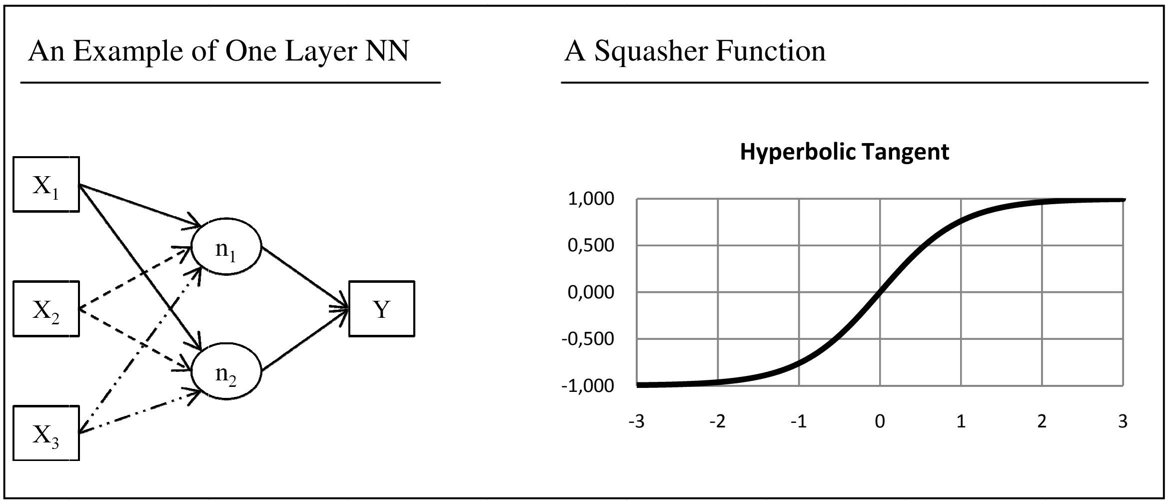

Figure: 10: An example of neural network and squasher function

The final result intended to be delivered from this study is to propose a balanced capital adequacy regime that may improve the overall efficiency of the financial intermediation.

Neural networks start with random seeds for connection between items in the network called synapses and iterate on the basis of minimizing the error. The beautiful thing about neural networks is not requiring any prior assumptions of the data, i.e. no need for normal distribution, equal variance-covariance matrices and so on. Neural networks can also capture non-linear relationships together with linear relationships, which is another important attribute. However, the commonly referred disadvantage of neural networks is that the relationships in the model are not easily interpretable. And as an iterative method, the model sometimes gets stuck in local optimums.

Neural Network 1

The first model is constructed with the five variables determined in the previous discriminant analysis. All variables are first standardized by subtracting means and dividing by standard deviation. Hyperbolic tangent is used as the squasher function or activation function. The first network has one hidden layer with five neurons where each variable and a constant or bias is connected to every neuron. The iteration starts from random numbers assigned to each connection or synapses. Six synapses are formed for each of the five neurons, and then the scores for each neuron enter the squasher function. Results from the squasher functions are connected two dependent variables, one for defaulters and one for none defaulters. Process is iterated for many times and stops when any of the following is satisfied:

- The relative change in training error or relative training error ratio reaches a minimum value, where the error is calculated by cross-entropy method, which is a logarithmic error calculation function
- Number of iterations reach the maximum value
- Fifteen minutes computation time

Scores of the dependent variables are then converted to pseudo probabilities by using a softmax function.

In order to reflect the importance of predicting defaults in the neural networks, the defaulters are coded as minus one hundred and non defaulters as one. This way, mispredicted defaulters will lead to higher errors, so that the network can trade in accuracy of non-defaulters for the accuracy of defaulters. Such coding values are determined by trial and error, seeking an improvement in the final results for the purpose of the analysis.

Batch training method is selected, where all data points pass through the model before updating synaptic weights. Although it was recommended for smaller datasets, it yielded the best results. The disadvantage of the batch training method is that it may need too much data passes until one of the stopping rules are met, however it directly minimizes the total error. Other types of training methods were the online method and the mini-batch method, where the online method updates synaptic weights after each and every data pass and the mini-batch method updates synaptic weights after a number of data passes.

Network type selected is the multilayer perception, which is the suggested model for financial data and classification problems. Scaled conjugate gradient optimization algorithm is used with the batch training method. All variables enter the model with chronological order to enhance the effects of the most recent data on the results. Finally, no testing or holdout sample was included in the first model. Below is the network diagram for the first model:

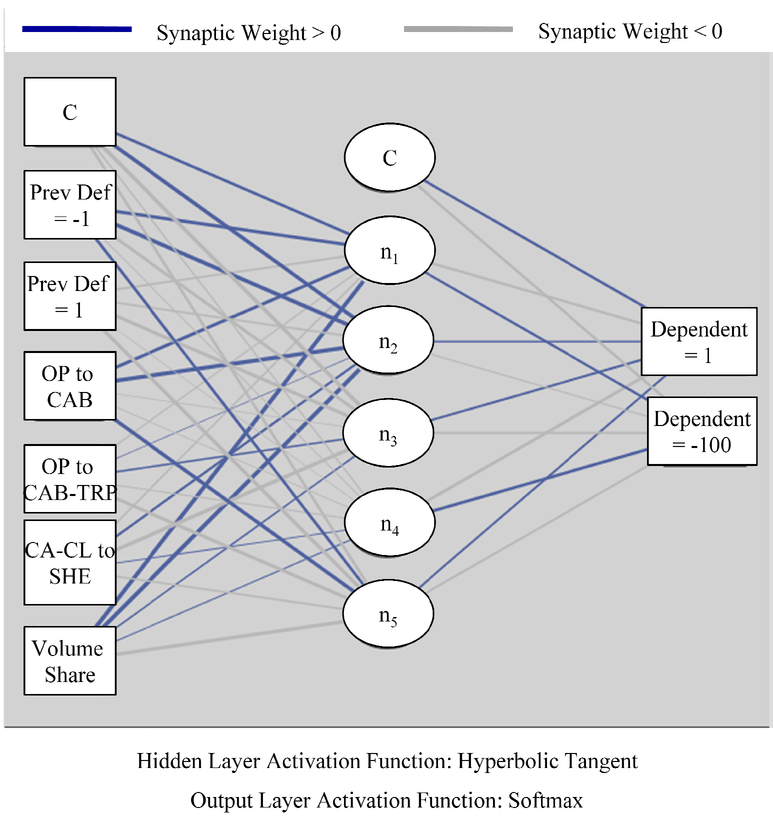

Figure 10: Model structure of Neural Network 1

One disadvantage of neural networks is that they can not reveal information about the importance or use of the independent variables in the model. Thus signs of the independent variables could not be assessed.

Table 19: Comparison of Discriminant Analysis and Neural Network 1 Classification Results

Discriminant Analysis

	DEP	DEF	NON-DEF	TOTAL
Count	DEF	90	46	136
	NON-DEF	645	2231	2876
%	DEF	66	33.8	100
	NON-DEF	22	77.6	100

Neural Networks

	DEP	DEF	NON-DEF	TOTAL
Count	DEF	112	24	136
	NON-DEF	720	2156	2876
%	DEF	82	17.6	100
	NON-DEF	25	75	100

Result of the first neural network in comparison with the final discriminant model is presented in Table 19 above. Default prediction of the neural network is superior, almost 25% better than the discriminant analysis and non-default predictions are slightly worse than the discriminant analysis. In order to have a better comparison of the both models, the chart for non-default versus default prediction for different cut off points is presented in Figure 11 below.

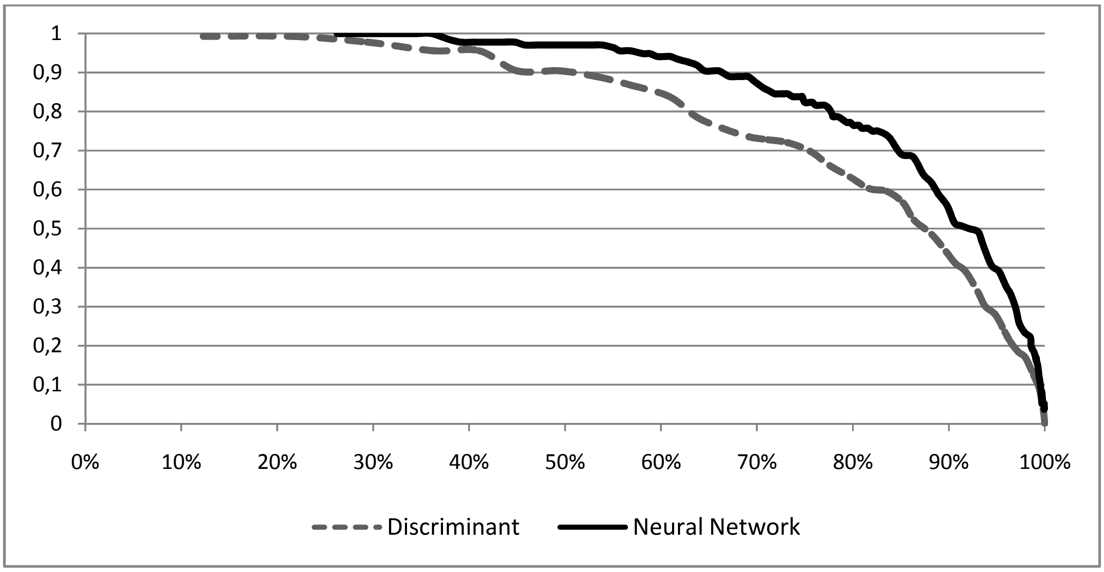

Figure 11: Discriminant analysis and neural classification results comparison for different cut-off points

Clearly neural networks better predicts defaulters for any given non-default prediction choice. Next, in order to check the reliability of the model, same holdout sample as used in discriminant analysis, for the period 7/2008 to 5/2009 is tested with another run of the same model.

Table 20: Comparison of Discriminant Analysis and Neural Networks Classification Results with Holdout Samples

Neural Network

		DEP	DEF	NON-DEF	TOTAL
Training	Count	DEF	105	23	128
		NON-DEF	778	1849	2627
	%	DEF	82	18	100
		NON-DEF	29.6	70.4	100
Holdout	Count	DEF	6	2	8
		NON-DEF	49	200	249
	%	DEF	75	25	100
		NON-DEF	19.7	80.3	100

Discriminant Analysis

		DEP	DEF	NON-DEF	TOTAL
Cases Selected	Count	DEF	90	38	128
		NON-DEF	652	1975	2627
	%	DEF	70.3	29.7	100
		NON-DEF	24.8	75.2	100
Cases Not Selected	Count	DEF	5	3	8
		NON-DEF	42	207	249
	%	DEF	62.5	37.5	100
		NON-DEF	16.9	83.1	100

Holdout performance of the neural network is again superior in terms of prediction of defaults and slightly worse in terms of prediction of non-defaults. Figure 12 shows the comparative graphs of the results of both. The neural network performs better in both sets of data, where difference is larger in the modeling data set.

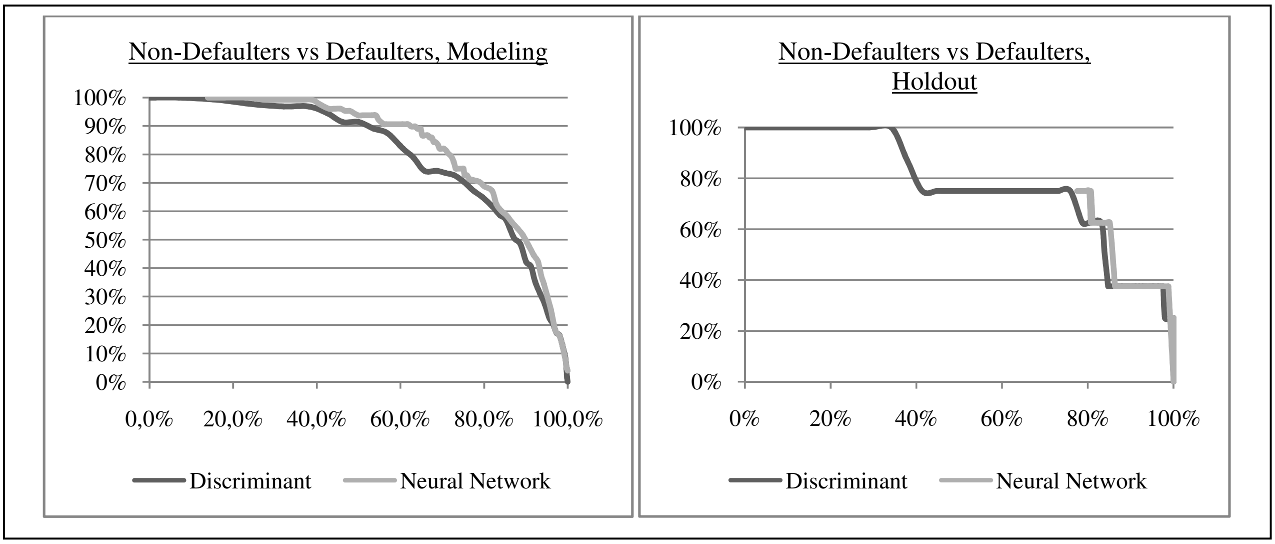

Figure 12: Comparison of discriminant analysis and neural networks classification results with holdout samples for different cut-off points

A Better Neural Network

A five neuron neural network outperforms discriminant analysis with the same independent variables. With the purpose of finding a better model, neural networks with different number of neurons and layers will be analyzed in this section and the results will be compared.

Increasing Number of Neurons

Four neural networks are constructed, with three, four, six and eight number of neurons and a single layer. Other than the number of neurons, model specifications are same as those of the Neural Network 1.

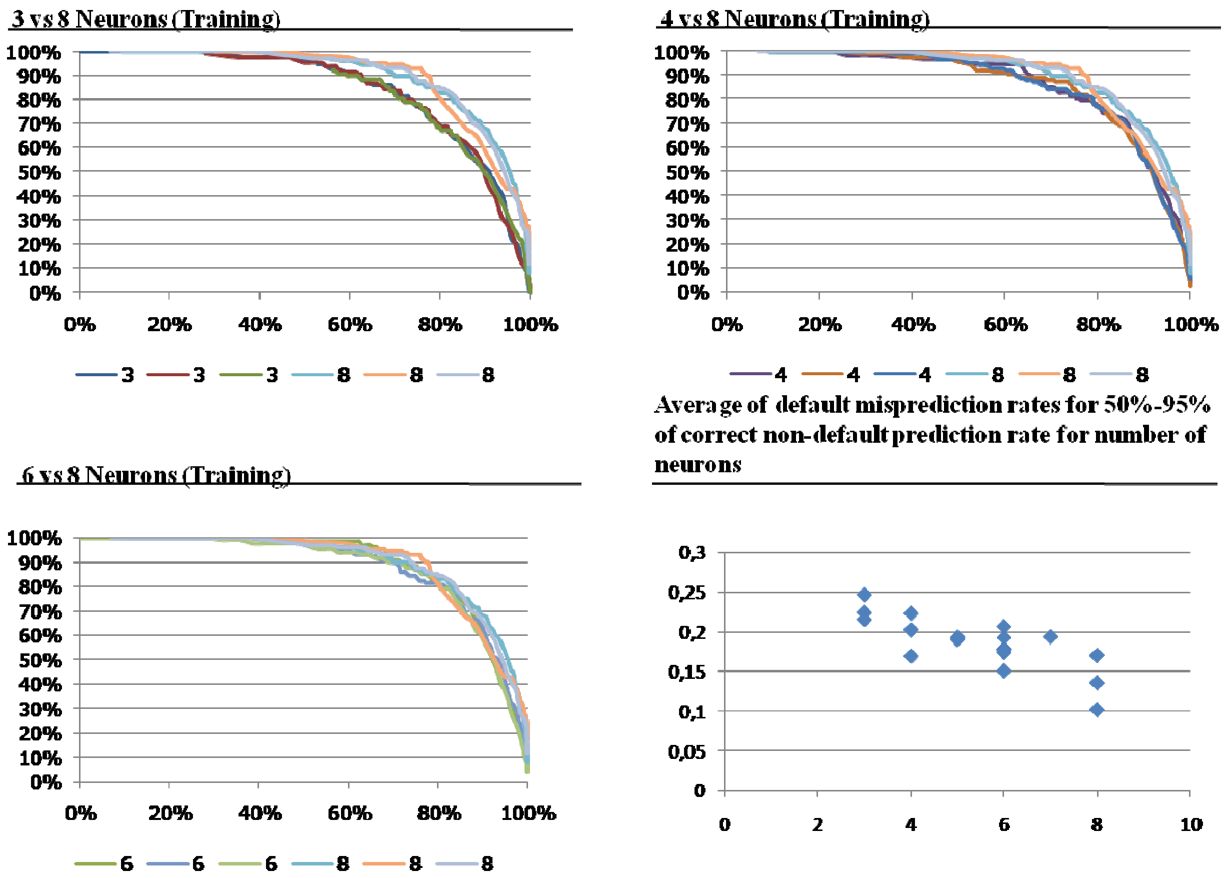

Figure 13: Performance of neural networks in the training sample with different number of neurons

The chart on the lower right of the Figure 13 with the title "Average of default misprediction rates for 50-95% of correct non-default prediction rate for number of neurons" is calculated through one minus the correct default prediction percentage for every matching non-default percentage between 50% and 95%. Each network had approximately eighty data points within that range. Each point on the graph is the average for a run of neural network analysis with specified number of neurons. As group sizes are highly different, with non defaulter group almost twenty times larger, the error calculated by the network is not the best indicator of performance. In order to account for the importance of the defaulters, such an error measurement as shown in Figure 13 above is developed.

Figure 13 also shows that, as the number of neurons increase, network performance also increases. Eight neurons are performing much better than three neurons, whereas the gap is closing as the number of neurons is increasing. The error graph on the other hand, confirms the trend as decreasing errors with increasing number of neurons.

Figure 14 below shows the performance of the networks with respect to holdout sample. Visual comparison shows that as number of neurons increase, performance of the networks in the holdout sample is unchanged or slightly worsened. The picture is reversed in the holdout samples, which points to signs of over fitting.

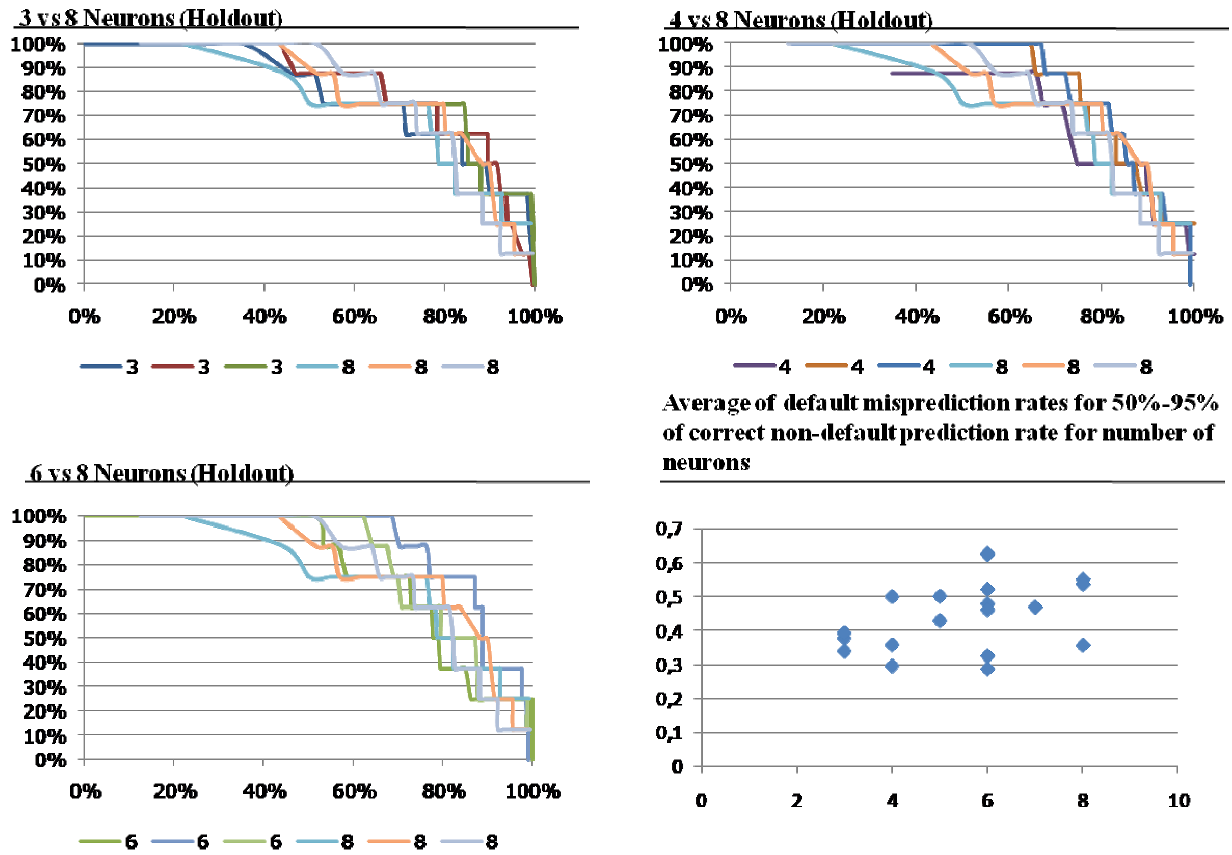

Figure 14: Performance of neural networks in the holdout sample with different number of neurons

<u>Increasing Number of Layers</u>

Next two layer networks with four neurons in the first layer and three neurons in the second layer are constructed with the same model specifications of the Neural Network 1.

Figure 15 shows the comparison of two layer network marked as “43” and “9” in the chart on the lower right.

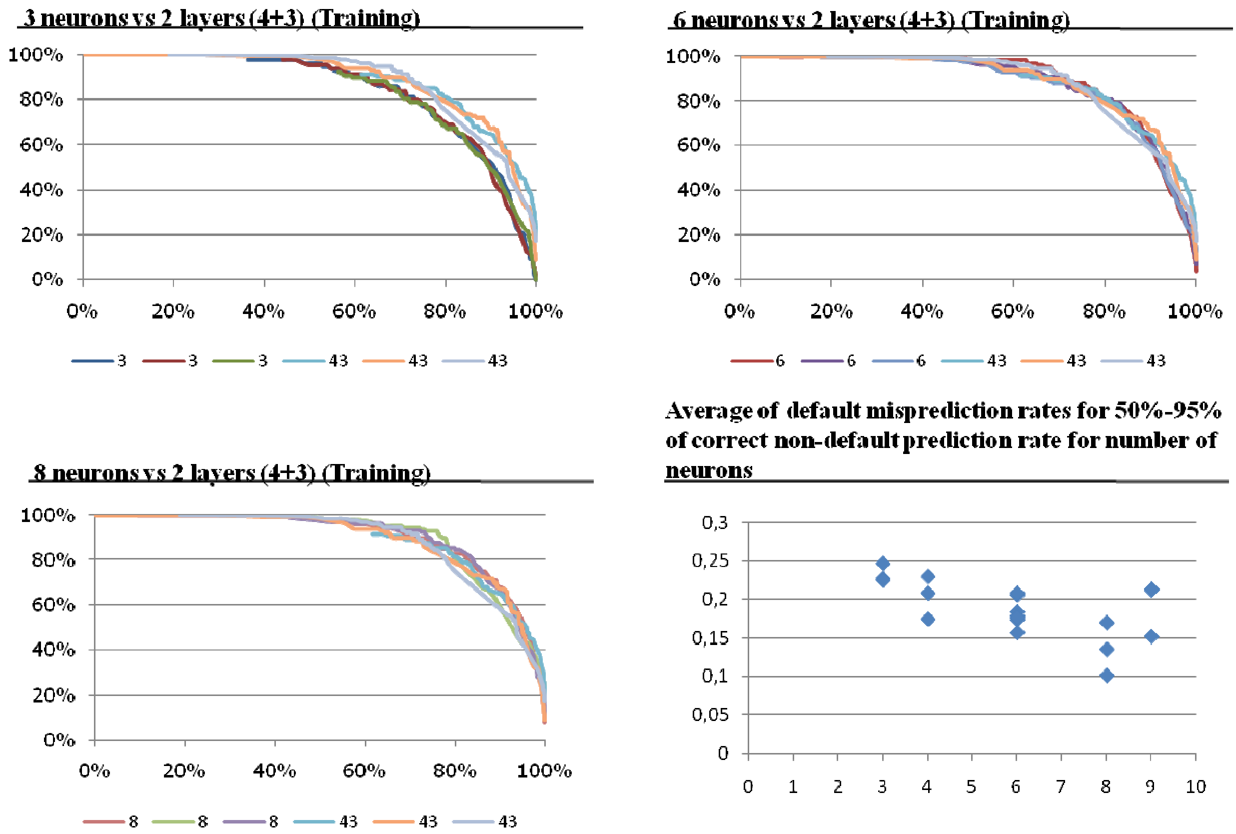

Figure 15: Performance of neural networks in the training sample with different number of neurons and layers

2 layer network with 4 neurons in the first and 3 neurons in the second layer performs better than 3 neurons, almost same with 6 neurons and slightly worse than 8 neurons. Chart showing error on the lower right also leads to same conclusion.

However, picture is opposite again for the holdout samples. As the network gets more complicated, holdout performance worsens, which is actually what matters. As shown in Figure 16, error figures of the two layer network are close to that of the 8 neuron network and way worse than the simple 3 neuron network. Adding another layer seems to do the same job as increasing the number of neurons for the purposes of this study.

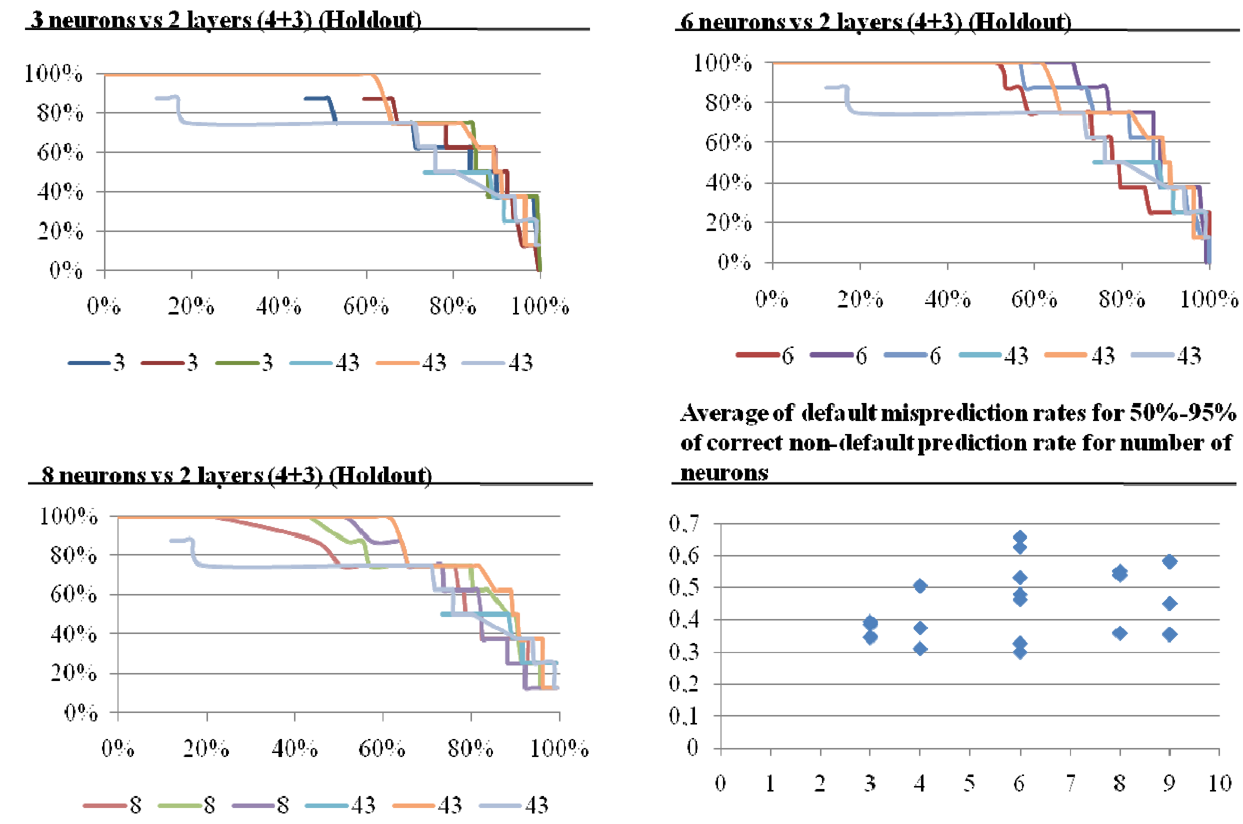

Figure 16: Performance of neural networks in the holdout sample with different number of neurons and layers

Adding the testing chunk

As signs of overtraining are present in neural network models, the solution is to introduce a testing sample, which is an independent set of data records used to track errors during training in order to prevent overtraining. Data points between 1/2006 and 6/2008 are selected as testing sample, whereas data points between 6/2008 and 5/2009 are selected as holdout. Results of 3 neuron network, 8 neuron network and 2 layer network with 4 and 3 neurons in first and second layers respectively are compared with the results of the same networks with testing sample. Rest of the model specifications is the same as Neural Network 1.

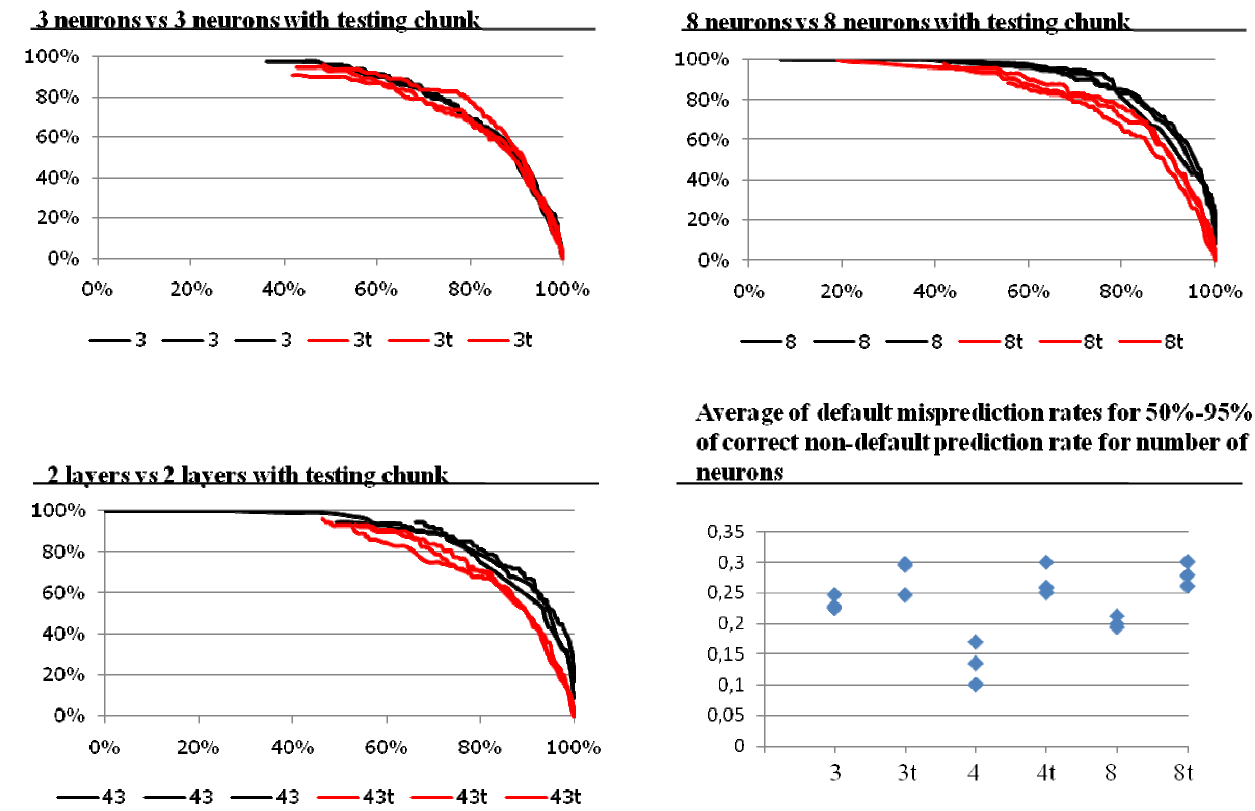

Figure 17: Performance of neural networks with testing chunk in the training sample with different number of neurons

Performance of the 3 neuron networks seem to be unaffected as shown on the comparison chart to the upper left of Figure 17 above. However on the misprediction graph, model with the testing chunk has higher error level. For 8 neuron networks and 2 layer networks, adding the testing chunk disturbs the performance of the networks on the training sample. The error chart on the lower right of Figure 17 also confirms the increased error levels of the models with the testing chunks. 2 layer network is marked as

"4" for the model without the testing chunk and "4t" for the one with the testing chunk in the error chart.

In the holdout sample, models with testing chunks are performing better. Results are very close for 3 neuron networks; however difference is clearer in 8 neuron and 2 layer networks as shown in Figure 18 below.

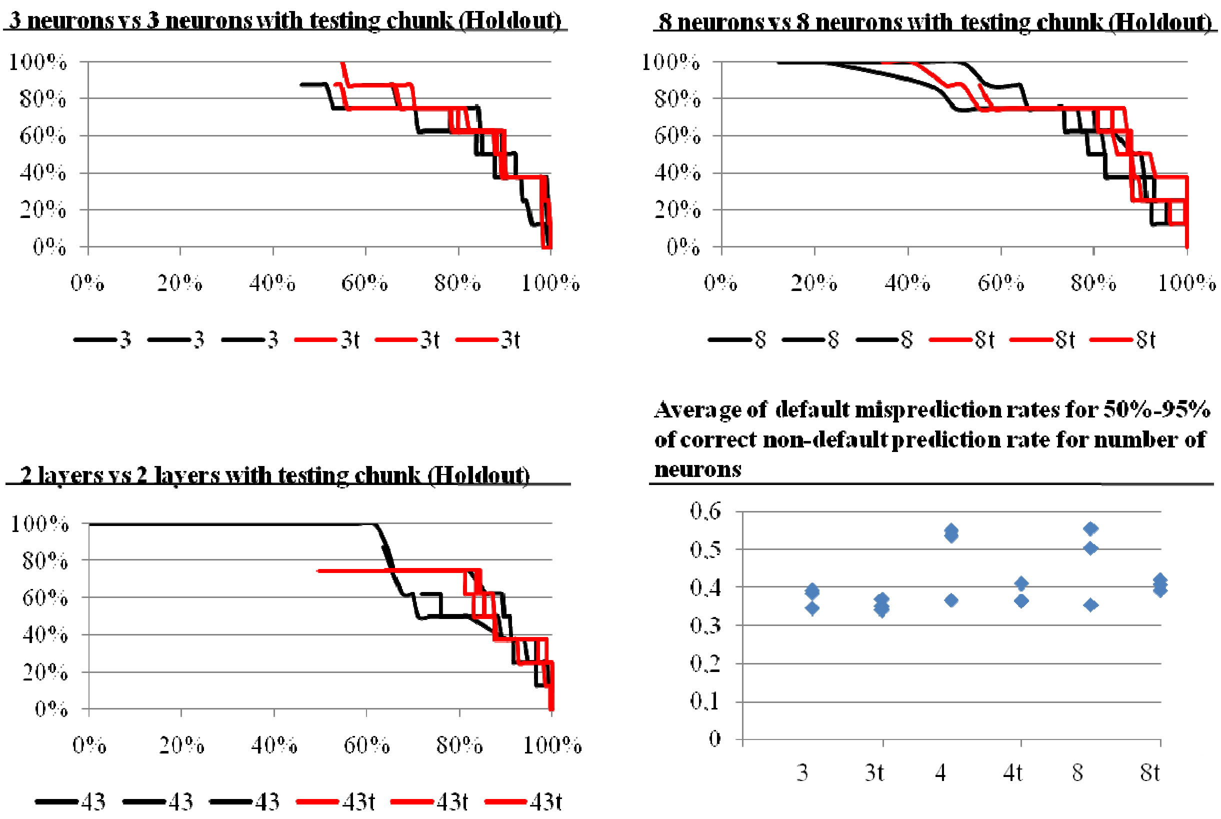

Figure 18: Performance of neural networks with testing chunk in the holdout sample with different number of neurons

Adding the testing chunk seems to improve holdout performance and lowers the trade-off between increased complexity and over fitting. Testing chunk also seems to lower the variation in re-runs of the networks, which can be observed from the lower dispersion of the errors of the models with testing chunks.

It can be concluded that, adding another layer or increasing number of neurons seems to cause over fitting, some of which can be partially remedied by adding the testing chunk. Thus, a one layer network with 3 to 5 neurons with the testing chunk seems to be the choice that is close to optimal.

Adding variables to increase model power

Multicollinearity in independent variables increases the risk of neural network to be stuck in local optimum or over train. In order to increase the variables in the analysis in search for capturing more of the variation in the dependent variable, following methodology is pursued:

- Correlation matrix is investigated and variables with high correlations are grouped
- From every correlated group, one variable is selected according to the explanatory power measured by Wilks' Lambda
- Explanatory power is judged through running multiple discriminant analysis with stepwise method and analyzing the F values
- Further theoretical judgment is used depending on the financial interpretation of the variables

The correlation matrix of the variables is shown in Table 21, and all of the correlations seem to be low enough from multicollinearity point of view.

Table 21: Correlation Matrix of the Variables Chosen

	OP to CAB	OP to CAB-TRP	AR to CL	AR to SHE-FA	CA to TD	CA-CL to SHE	DCAB to TA	FA to SHE	CPR to CAB	TRP to CAB	TL to TA	VSc	V to CAB	VS	TRPc	Prev Def
OPtoCAB	1,00	0,25	-0,11	0,08	-0,17	-0,12	-0,05	0,31	0,05	0,27	0,34	-0,01	0,29	-0,01	0,03	-0,21
OPtoCAB-TRP	0,25	1,00	-0,03	0,03	-0,04	-0,05	-0,01	0,13	0,22	0,37	0,15	0,00	0,08	0,03	0,03	-0,03
ARtoCL	-0,11	-0,03	1,00	0,01	0,12	0,14	0,00	0,00	-0,07	-0,10	-0,08	0,01	-0,08	-0,04	-0,01	0,03
ARtoSHE-FA	0,08	0,03	0,01	1,00	0,01	0,00	-0,01	0,05	-0,02	0,06	0,07	-0,01	0,03	0,00	0,00	-0,03
CAtoTD	-0,17	-0,04	0,12	0,01	1,00	0,10	0,01	-0,12	0,01	-0,06	-0,26	0,02	-0,09	-0,04	0,00	-0,02
CA-CLtoSHE	-0,12	-0,05	0,14	0,00	0,10	1,00	0,03	-0,35	-0,18	-0,12	0,09	0,00	-0,06	0,00	0,01	0,01
DCABtoTA	-0,05	-0,01	0,00	-0,01	0,01	0,03	1,00	-0,08	0,00	-0,03	-0,01	-0,05	0,00	0,01	0,01	0,00
FAtoSHE	0,31	0,13	0,00	0,05	-0,12	-0,35	-0,08	1,00	0,00	0,26	0,06	-0,02	0,12	0,02	0,00	-0,02
CPRtoCAB	0,05	0,22	-0,07	-0,02	0,01	-0,18	0,00	0,00	1,00	0,56	0,00	0,00	0,01	0,00	0,06	-0,01
TRPtoCAB	0,27	0,37	-0,10	0,06	-0,06	-0,12	-0,03	0,26	0,56	1,00	0,44	-0,01	0,15	0,02	0,08	-0,14
TLtoTA	0,34	0,15	-0,08	0,07	-0,26	0,09	-0,01	0,06	0,00	0,44	1,00	-0,02	0,22	0,01	0,01	-0,15
VSc	-0,01	0,00	0,01	-0,01	0,02	0,00	-0,05	-0,02	0,00	-0,01	-0,02	1,00	0,00	0,08	0,01	0,02
VtoCAB	0,29	0,08	-0,08	0,03	-0,09	-0,06	0,00	0,12	0,01	0,15	0,22	0,00	1,00	0,42	0,00	-0,13
VS	-0,01	0,03	-0,04	0,00	-0,04	0,00	0,01	0,02	0,00	0,02	0,01	0,08	0,42	1,00	-0,01	0,03
TRPc	0,03	0,03	-0,01	0,00	0,00	0,01	0,01	0,00	0,06	0,08	0,01	0,01	0,00	-0,01	1,00	0,02
PrevDef	-0,21	-0,03	0,03	-0,03	-0,02	0,01	0,00	-0,02	-0,01	-0,14	-0,15	0,02	-0,13	0,03	0,02	1,00

Next, in order to check the stability of the ratios and see whether any variables are performing better in one period, the dataset is divided into four chunks. Stepwise discriminant analysis is run for each period with the eleven variables. Statistics for the four periods are shown in Table 22 below.

Table 22: Statistics for Periods

Dates	Period	Number of Defaulters	%	Number of Non-Defaulters	%	Total
1/99 - 6/01	2,5 years	41	5,80%	664	94,20%	705
6/01 - 2/03	2,5 years	44	6,10%	681	93,90%	725
12/03- 06/06	2,5 years	18	2,30%	756	97,70%	774
06/06- 5/09	3,5 years	33	4,10%	775	95,90%	808
1/99-05/09	10,5 years	136	4,50%	2876	95,50%	3012

As shown in APPENDIX F: SIGNIFICANT VARIABLES IN DIFFERENT PERIODS, explanatory variables are not stable over time, different variables entered the discriminant function in different periods.

Table 23: Significant Classifiers in Different Periods

1/1999 - 6/2001	6/2001 - 12/2003	12/2003 - 6/2006	6/2006 - 5/2009	1/1999-5/2009
CPRtoCAB	OPtoCAB	OPtoCAB	ΔCABtoTA	OPtoCAB
PrevDef	OPtoCAB-TRP	TRPtoCAB	OPtoCAB	PrevDef
FAtoSHE	CA-CLtoSHE	CPRtoCAB	PrevDef	OPtoCAB-TRP
ΔCABtoTA			TRPc	CA-CLtoSHE
			CAtoTD	VS

3 months operating expenses to capital adequacy base ratio appears in three sub periods and the whole period. Volume Share does not enter in any of the sub periods but is significant for the whole period. For the periods considered,

(i) ΔCAB to TA

(ii) FA to SHE

(iii) CPR to CAB

(iv) TRP to CAB

(v) TRPc

(vi) CA to TD

are not present in the model covering the whole analysis period, but appear in the sub periods. Correlation do not show any jumps that needs reconsideration from multicollinearity side, in all of the sub periods.

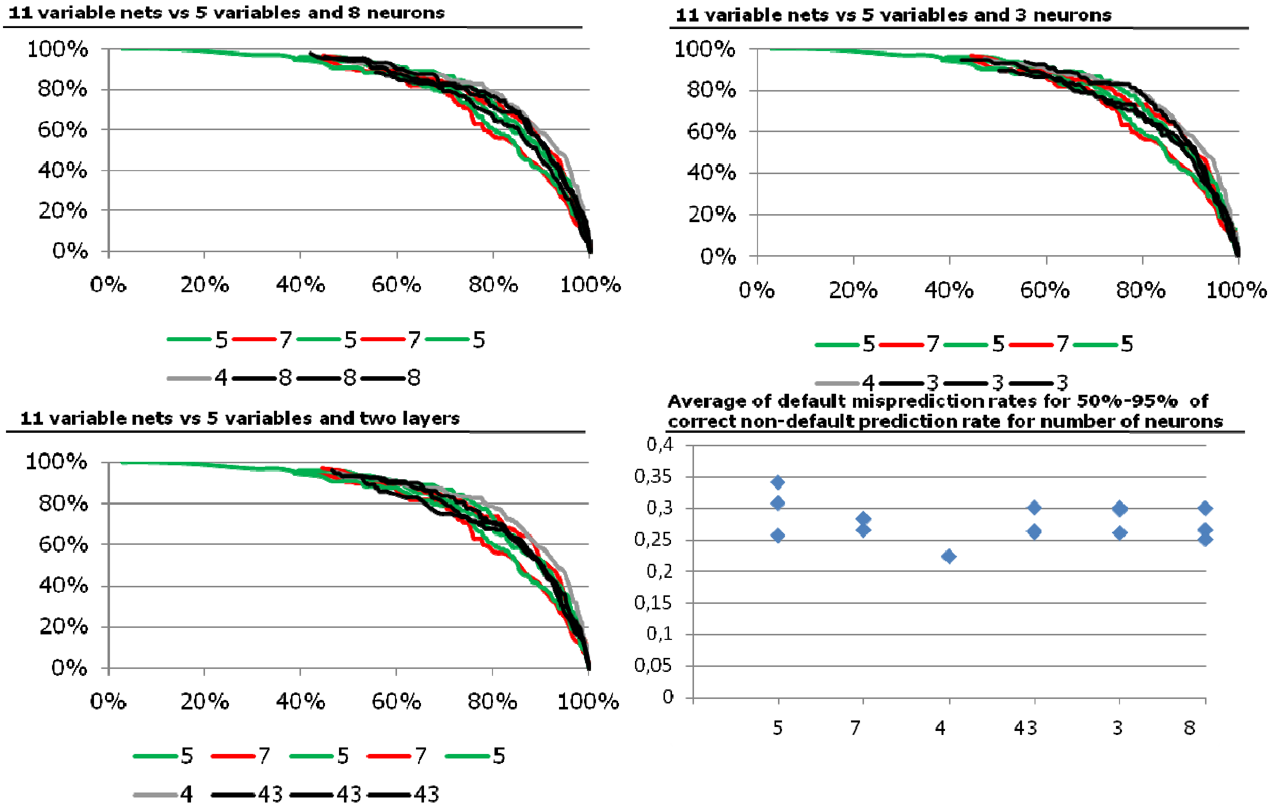

Figure 19: Performance of neural networks with different number of variables in the training sample with different number of neurons and layers

Comparison of the networks with different number of variables is shown in Figure 19 above. Eleven variables are run with four, five and seven neurons and compared to 5-Variable models with three and eight neurons and two- layer network with four neurons in the first layer and three neurons in the second. Increasing number of variables does not seem to improve the training results considerably. Model with four neuron and eleven variables posted the minimum error, and as can be seen from the graphs, is the best performer.

Performance of the models in the holdout sample is shown in Figure 20 below. Network with eleven variables and five neurons posts the worst results, although it was the average performer in the training dataset. Visual inspection of the charts in Figure 20 shows that 11 - variable networks are not making a difference in holdout samples.

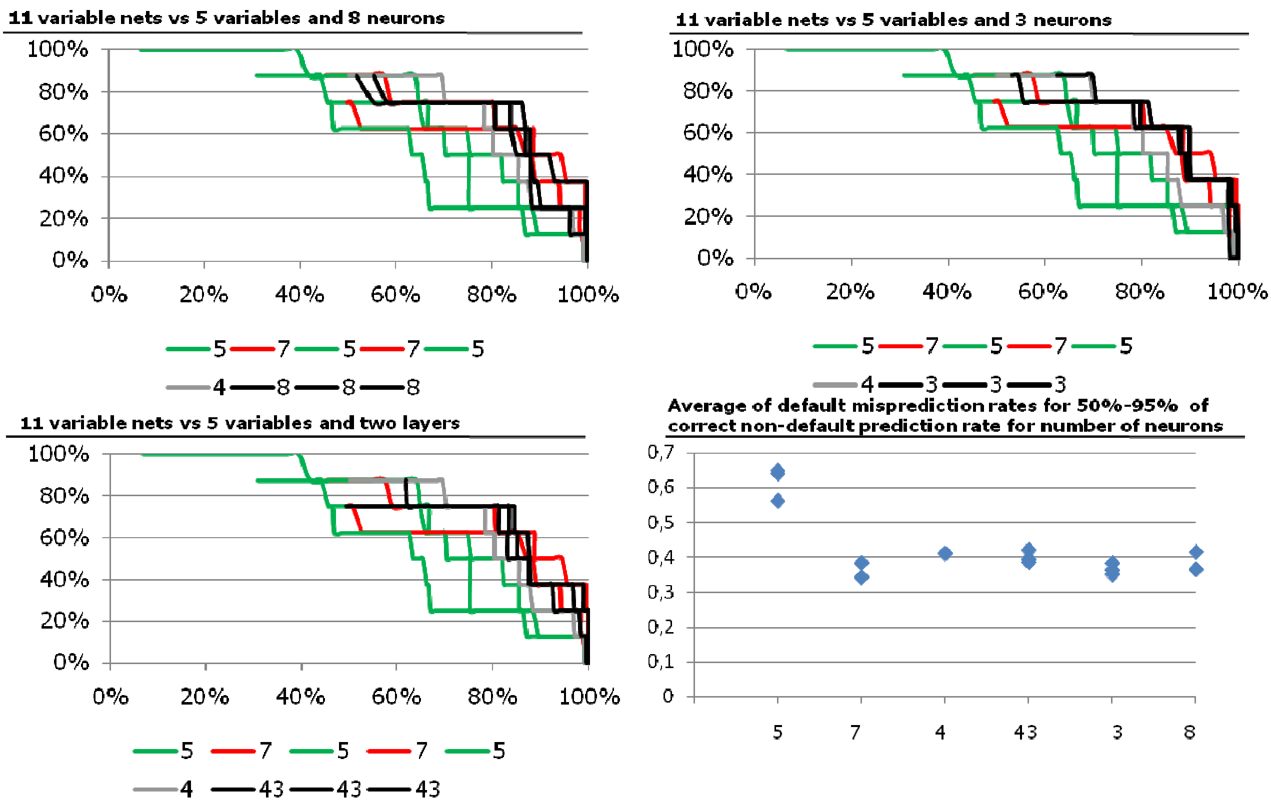

Figure 20: Performance of neural networks with different number of variables in the holdout sample with different number of neurons and layers

Final Model

In terms of determining the optimum network structure, results of the search for a better network model can be summarized as:

- Increasing number of neurons improves the training results, however at the cost of over fitting, as observed from the holdout tests
- Adding additional layers leads to similar results as increasing number of neurons.
- Adding testing chunks seem to improve holdout performances of any model

In terms of increasing number of variables, the summary of results are:

- After taking care of multicollinearity, six more variables revealed through dividing the data into four time periods, and addition of these variables to the model leads to slightly better results in training samples, however little worse performance is observed in holdout samples
- Instead of adding six more variables, addition of less of these variables in different combinations are also tested and results do not show considerable improvement

It is observed that increasing the complexity of the network leads to signs of over fitting, as holdout performances are getting worse. Increasing number of variables does not improve the results compared to the complexity brought in. As per the parsimony principle, the most suitable network may be the one with five variables and constructed with three or four neurons and one layer.

Finally, factor analysis is used to extract uncorrelated components. Eleven components are extracted and they explain approximately 80% of the variance. However, using these components as independent variables does not contribute to the results at all.

Using the five variables directly seems better, as per the parsimony principle. Varimax rotated components are shown in APPENDIX G: FACTOR ANALYSIS RESULTS.

Final network model is constructed with five variables, and tree neurons. In order to prevent overtraining, data points between 1/2006 and 6/2008 are selected as testing sample. Once again, the holdout sample is formed by data points between 7/2008 and 5/2009. Defaulters have the value of -100 and non-defaulters have the value of 1. Multilayer perceptron neural network with scaled conjugate gradient optimization algorithm is specified with batch training.

Parameter estimates of the final model are presented in Table 24 below. The signs and significances of the parameters are very difficult to analyze, which is one of the important shortcomings of neural networks.

Table 24: Parameter Estimates of the Final Neural Network

		Predicted				
		Hidden Layer 1			Output Layer	
Predictor		H(1:1)	H(1:2)	H(1:3)	DEFAULT	NON-DEFAULT
Input Layer	(Bias)	-1.22	-0.514	-0.023		
	[PrevDefaults=-1]	-0.124	0.379	-0.291		
	[PrevDefaults=1]	-0.392	-0.3	-0.079		
	OP to CAB	0.234	-0.33	-0.394		
	OP to CAB – TRP	0.017	-0.064	-1.129		
	VolumeShare	0.357	-0.55	1.275		
	CA-CL to SHE	-0.968	-0.235	-0.095		
Hidden Layer 1	(Bias)				-1.62	1.189
	H(1:1)				0.607	-0.793
	H(1:2)				0.094	-0.838
	H(1:3)				-1.293	1.409

The calculation steps from financial ratios to pseudo probabilities are as follows:

(i) All financial ratios are standardized by subtracting the mean and dividing by the standard deviation

(ii) The matrix with all standardized variables is then multiplied by the synaptic weights of each neuron one by one

(iii) All of the results are transformed by a squasher function, which was selected as hyperbolic tangent

(iv) Transformed matrices are then multiplied by the output layer's synaptic weights and separate scores are calculated for each of the groups

The steps described above leads to the following equation:

$$\boxed{tanh\left(\begin{bmatrix} \cdot \\ Standardized \\ Variables \\ \cdot \end{bmatrix} X \begin{bmatrix} \cdot \\ Input\ Layer \\ Synaptic\ Weights \\ \cdot \end{bmatrix}\right) X \begin{bmatrix} \cdot \\ Output\ Layer \\ Synaptic\ Weights \\ \cdot \end{bmatrix} = \begin{bmatrix} \cdot \\ Result \\ Matrix \\ \cdot \end{bmatrix}}$$

The result matrix is converted to pseudo probabilities with softmax function, $\frac{e^a}{e^a+e^b}$

Practical Implication

Classification results of the final network is presented in Table 25 for the cut-off score of 0,95. The cut-off score selected is too high because most of the results were packed close to 1. Different variations of dependent variable specification are tested for even dispersion of results among the 0-1 scale, however this can not be achieved. However, at the bottom line, the performance of the model is satisfactory with the current setting.

Table 25: Classification Results for the Final Neural Network

		DEP	DEF	NON-DEF	TOTAL
Training	Count	DEF	95	33	128
		NON-DEF	676	1951	2627
	%	DEF	74	26	100
		NON-DEF	26	74	100
Holdout	Count	DEF	6	2	8
		NON-DEF	43	206	249
	%	DEF	75	25	100
		NON-DEF	17	83	100

In the final model, three out of four defaulters and three out of four non defaulters are classified correctly in both training and holdout samples except that prediction rate of non-defaulters in the holdout sample is higher at 83%. It shall be noted that this model is predicting the pre-default event of capital requirement breach, which is theoretically more difficult than predicting default itself. Thus, these results for predicting pre-default can be considered successful.

Data points that have a score higher than 0.95 are 95 defaulters and 676 non defaulters, which lead to a group with 12.3% default level. Data points that have a lower score than 0.95 lead to a group with 33 defaulters and 1951 non-defaulters, result in a group with 1.6% default level. The analysis divides the intermediary institutions into two groups where one of the groups have 10 times higher default risk than the other. For the holdout sample, the high risk group has 12.2% default ratio whereas the low risk group has 1.0%. For practical implications, desired levels of default can be set through adjusting the cut-off point. Sensitivity of the cut-off point with respect to risk percentage of the groups is provided in Figure 21 below.

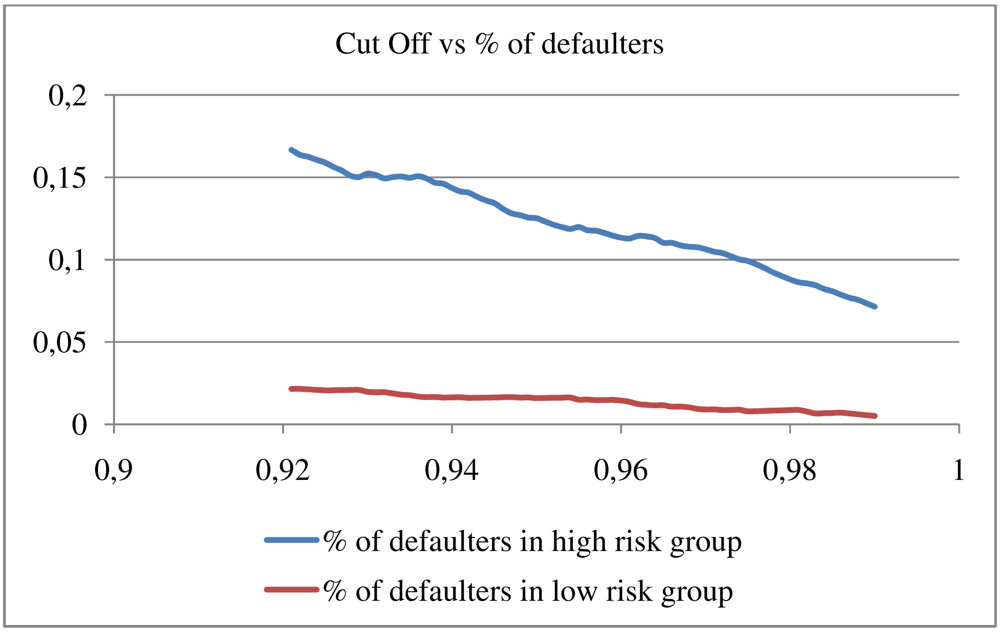

Figure 21: Low risk and high risk rates for different cut off points

Predictive Power

For the calculation of the final model, the dataset is formed by calculating the average of past three months figures for each data point. Although this method accounts for a time component to detect the defaulters early, another dataset is constructed to analyze how early the model can generate a signal. In the second dataset, average of past six months to three months is calculated for a data point. Instead of 136 default of the former dataset, the latter has 120.

The results of the former dataset are marked with “f” and that of the new dataset are marked with “p” as shown in Figure 22 below. As expected, the latter dataset performs slightly worse than the former dataset in both training and holdout samples. Network for the latter dataset also has tree neurons and one layer.

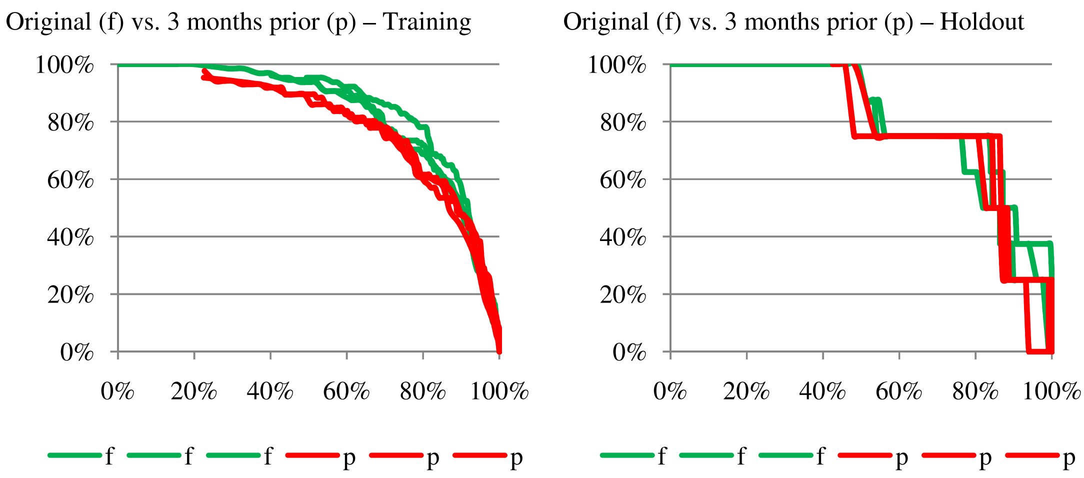

Figure 22: Comparison of accuracy of the 3-month prior to default dataset with the original dataset

Errors are shown in Figure 23 below and results of holdout samples and training samples of both datasets are compared. “1” and “2” on the x-axis corresponds to error levels of the training and holdout samples of the former dataset, whereas “3” and “4” stands for the error levels of training and holdout samples of the latter dataset respectively in Figure 23.

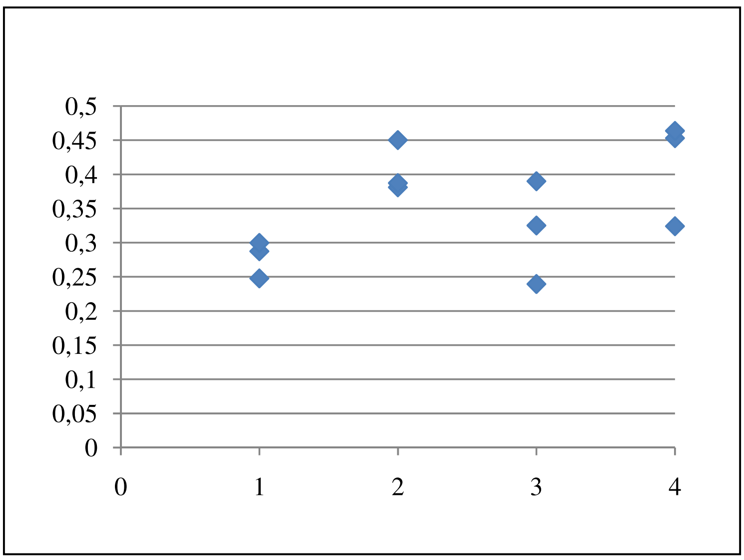

Figure 23: Comparison of misprediction rates of the 3-month prior to default dataset with the original dataset

Error levels also show that the difference between the former and latter datasets are close enough to conclude that the model is well specified and has the potential to detect the defaults at least 3 months prior to default.

CHAPTER 5

CONCLUSION

Capital Adequacy Reports designed by CMB were very precious for the overall success of the models presented in thus study. The database benefits a lot from industry specific details available in very high frequency, monthly, bi-weekly and weekly, which provides detailed information on the financial status of the intermediary institutions. CARs are tailored specifically to monitor intermediary institution industry, and proved quite useful as apparent from the satisfactory prediction rates of the models.

Current scheme of regulations and system are very competent, evident from the very low default rates in the intermediary institution industry. In order to contribute to the efforts to improve the current regulations, prediction of Capital Adequacy Base deficiency was selected as dependent variable, which was a pre-default measure. Using three month average of each ratio leads to smoothening of the outliers and contributed to the further earlier signaling of the occurrence of financial distress. Although such choice of dependent variable yielded sufficient data for the analysis, the detection of "pre-default" was more difficult than predicting default.

Neural Networks, which do not have any assumptions regarding the data, performed better than Discriminant Analysis that has a number of prior data requirements not met by the available dataset. However, both Discriminant Analysis and Neural Networks successfully detected the pre-default events, comparable to the accuracy of default prediction literature. Both models had sufficient reliability, as shown by the holdout sample accuracy.

Another important finding was that the independent variables that explain the variance are not stable over time, thus the model shall be updated at least annually for practical implications. Increasing importance of financial intermediation industry for the economic growth of Turkey may in turn benefit from the modification of some of the already successful regulations with insights from this study.

Not only the financial intermediation industry, but the methods used in this study may also be of use for the prediction of financial distress for the companies from other industries. Application of similar methods to insurance industry, banking industry or personal credit scoring shows satisfactory results in the literature. Predicting financial distress in real sector companies through the methods that is similar to this study may also be handy for the corporate credit officers of banks. Quality of the loans extended by banks are expected to be monitored in a much more tighter fashion, where such analysis may help these efforts in terms of both monitoring and taking initial credit extension decisions.

APPENDIX A: INTERMEDIARY INSTITUTIONS IN TURKEY

NO.		NON BANK INTERMEDIARIES	PAID IN CAPITAL (TRY)	BROKERAGE	UNDERWRITING	PORTFOLIO MAN.	INVESTMENT CONS.	REPO	MARGIN TRADING	DERIVATIVE CONT.
1	-	ACAR	2,540,000	*	*	*	*	*	*	*
2	-	AKDENİZ (*)	1,210,000	*					*	*
3	-	ALAN YATIRIM	1,100,000	*	*		*		*	*
4	-	ALFA (*)	5,100,470	*						
5	-	ALTAY YATIRIM (*)	335,000	*					*	
6	-	ARTI (*)	225,000	*						
7	-	ATA YATIRIM	19,600,000	*	*	*	*	*	*	*
8	-	ATAONLİNE	1,100,000	*	*		*	*	*	*
9	-	AYBORSA	1,000,000	*					*	
10	-	B.A.B. (*)	1,375,000	*					*	
11	-	BAHAR	1,000,000	*					*	
12	-	BAŞKENT	2,000,000	*					*	*
13	-	BGC PARTNERS	7,000,000	*			*	*	*	*
14	-	BİZİM (4)	3,000,000	*	*	*	*	*	*	*
15	-	CAĞDAS	3,200,000	*					*	
16	-	CAMİŞ	300,000	*	*			*	*	*
17	-	CENSA	200,000	*					*	
18	-	CREDIT AGRICOLE CHEUVREUX	5,125,000	*					*	*
19	-	CREDİT SUISSE İSTANBUL	5,761,000	*		*	*		*	*
20	-	DARUMA (*)	3,000,000	*	*		*		*	
21	-	DEĞER (*)	1,150,000	*					*	
22	-	DEHA	90,000	*				*		
23	-	DELTA	7,200,000	*	*	*	*	*	*	*
24	-	DUNYA	650,000	*					*	
25	-	ECZACIBASI	11,000,000	*	*	*	*	*	*	*
26	-	EFG İSTANBUL	8,450,000	*	*	*	*	*	*	*
27	-	EGEMEN	1,100,000	*					*	*
28	-	EKİNCİLER YATIRIM	2,054,000	*	*	*	*	*	*	*
29	-	ENTEZ	2,000,000	*					*	*
30	-	ETİ YATIRIM	7,200,000	*	*	*	*	*	*	
31	-	EURO YATIRIM	7,000,000	*	*	*	*	*	*	*
32	-	EVGİN YATIRIM	2,420,000	*		*		*	*	*
33	-	GALATA	4,500,000	*	*		*		*	*
34	-	GEDİK YATIRIM	23,000,000	*	*	*	*	*	*	*

NO.		NON BANK INTERMEDIARIES	PAID IN CAPITAL (TRY)	BROKERAGE	UNDERWRITING	PORTFOLIO MAN.	INVESTMENT CONS.	REPO	MARGIN TRADING	DERIVATIVE CONT.
35	-	GFC GENERAL FİNANS	3,000,000	*					*	*
36	-	GLOBAL	17,500,000	*	*	*	*	*	*	*
37	-	GÜNEY	750,000	*					*	
38	-	GÜVEN	500,000	*				*	*	*
39	-	HAK	1,000,000	*	*	*		*	*	*
40	-	HEDEF (*)	2,500,000	*					*	*
41	-	İNFO YATIRIM	1,500,000	*	*	*	*	*	*	*
42	-	K (*)	7,000,000	*					*	
43	-	KAPİTAL YATIRIM	7,000,000	*	*			*	*	*
44	-	LEHMAN BROTHERS (*)	7,000,000	*	*	*	*	*	*	
45	-	MARBAŞ	5,000,000	*					*	*
46	-	MED (*)	200,000	*					*	
47	-	MEKSA YATIRIM	7,100,000	*	*	*	*	*	*	*
48	-	MERKEZ (*)	6,500,000	*		*			*	
49	-	METRO YATRIM	7,000,000	*	*	*	*	*	*	
50	-	MORGAN STANLEY (*)	13,500,000	*	*		*		*	*
51	-	CITI	2,000,000	*			*	*	*	*
52	-	ORION INVESTMENT	10,000,000	*	*	*	*	*	*	*
53	-	OYAK (2)	38,540,000	*	*	*	*	*	*	*
54	-	ÖNCÜ	3,000,000	*		*			*	*
55	-	ÖNER	4,500,000	*					*	
56	-	PAY	400,000	*					*	*
57	-	PİRAMİT	3,500,000	*					*	
58	-	POLEN	2,280,000	*					*	
59	-	PRİM	750,000	*					*	*
60	-	RAYMOND JAMES (*) (3)	1,984,000	*						
61	-	UNICREDIT	7,500,000	*						
62	-	SANKO	2,500,000	*	*	*	*	*	*	*
63	-	SARDİS	900,000	*					*	
64	-	SAYILGAN	1,000,000	*					*	
65	-	SOYMEN	6,000,000	*					*	
66	-	STANDARD ÜNLÜ	2,683,330	*	*	*	*	*	*	*
67	-	KARE YATIRIM	7,000,000	*	*	*	*	*	*	*
68	-	STRATEJİ	3,000,000	*	*	*	*	*	*	*
69	-	TACİRLER	7,500,000	*	*	*	*	*	*	*
70	-	TAKSİM YATIRIM	1,000,000	*	*	*	*	*	*	*
71	-	TERA	2,280,000	*					*	*
72	-	TİCARET YATIRIM	9,205,034	*			*	*	*	

NO.		NON BANK INTERMEDIARIES	PAID IN CAPITAL (TRY)	BROKERAGE	UNDERWRITING	PORTFOLIO MAN.	INVESTMENT CONS.	REPO	MARGIN TRADING	DERIVATIVE CONT.
73	-	TOROS TİCARET	1,650,000	*					*	*
74	-	UBS	9,000,000	*			*	*	*	
75	-	ULUS	1,000,000	*					*	
76	-	ÜNİVERSAL	2,000,000	*						
		Total:	360,207,834	76	31	28	33	34	70	45

(*) Temporarily closed

NO.		BANK OWNED INTERMEDIARIES	PAID IN CAPITAL (TRY)	BROKERAGE	UNDERWRITING	PORTFOLIO MAN.	INVESTMENT CONS.	REPO	MARGIN TRADING	DERIVATIVE CONT.
1	-	ADA	500,000	*						
2	-	AK	50,000,000	*	*	*	*	*	*	*
3	-	ALTERNATİF	6,500,000	*	*	*	*	*	*	*
4	-	ANADOLU	5,400,000	*	*	*	*	*	*	
5	-	DENİZ	25,000,000	*	*	*	*	*	*	*
6	-	DENİZTÜREV	8,000,000	*		*	*	*	*	*
7	-	DEUTSCHE	2,000,000	*	*		*	*	*	*
8	-	EKSPRES	950,000	*	*	*	*	*	*	*
9	-	FİNANS	12,000,000	*	*	*	*	*	*	*
10	-	FORTİS	18,100,000	*	*	*	*	*	*	*
11	-	GARANTİ	8,327,648	*	*	*	*	*	*	*
12	-	HALK	20,150,000	*	*	*	*	*	*	*
13	-	HSBC	7,000,000	*	*	*	*	*	*	*
14	-	İŞ	45,000,000	*	*	*	*	*	*	*
15	-	KALKINMA	5,000,000	*	*	*	*	*	*	*
16	-	MERRILL LYNCH	375,000	*			*		*	
17	-	NUROL	3,000,000	*					*	*
18	-	POZİTİF	3,000,000	*	*	*	*		*	*
19	-	ŞEKER	12,000,000	*	*	*	*	*	*	*
20	-	TAİB	1,750,000	*	*	*	*	*	*	
21	-	TEB	10,000,000	*	*	*	*	*	*	*
22	-	TEKSTİL	5,000,000	*	*	*	*	*	*	*
23	-	TURKİSH	4,400,000	*	*	*	*	*	*	*
24	-	UNICORN	21,600,000	*	*		*	*	*	
25	-	VAKIF	6,000,000	*	*	*	*	*	*	*
26	-	YAPI KREDİ	98,918,083	*	*	*	*	*	*	*
27		YATIRIM FİNANSMAN	38,500,000	*	*	*	*	*	*	*
28	-	ZİRAAT	11,000,000	*	*	*	*	*	*	*
		Total:	429,470,731	28	24	23	26	24	27	23
		Grand Total: (Bank + Non Bank)	789,678,565	104	55	51	59	58	97	68

APPENDIX B : TESTS OF NORMALITY

Tests of Normality, Raw Data, All Data

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,398	,000	,146	,000
OP to CAB	,117	,000	,874	,000
OP to CAB - TRP	,398	,000	,123	,000
AR to CL	,312	,000	,303	,000
AR to SHE-FA	,427	,000	,096	,000
CA to CL	,408	,000	,149	,000
CA to SHE	,185	,000	,728	,000
CA to TA	,083	,000	,836	,000
CA to TD	,386	,000	,176	,000
CA-CL to SHE	,120	,000	,631	,000
CL to SHE	,209	,000	,696	,000
ΔCAB to TA	,355	,000	,061	,000
FA to SHE	,130	,000	,880	,000
CPR to TRP	,378	,000	,264	,000
CPR to CAB	,365	,000	,387	,000
NWC to TA	,048	,000	,902	,000
ΔSHE to TA	,431	,000	,020	,000
PR to TRP	,300	,000	,384	,000
PR to CAB	,156	,000	,810	,000
TRP to CAB	,165	,000	,773	,000
TRP + OP to CAB	,114	,000	,893	,000
SHE - TL to TL	,377	,000	,167	,000
SHE to TA	,080	,000	,958	,000
Δ(CAB-TRP) to TA(SHE-CAB)	,372	,000	,047	,000
TL to SHE - FA	,465	,000	,039	,000
TL to CAB	,198	,000	,715	,000
TL to TA	,081	,000	,867	,000
ΔVS	,441	,000	,111	,000
V to CA	,301	,000	,355	,000
V to SHE-FA	,284	,000	,479	,000
V to CAB	,262	,000	,490	,000
VS	,359	,000	,319	,000
ΔV	,462	,000	,138	,000
CAB to TA	,047	,000	,984	,000
ΔTRP	,434	,000	,048	,000

Tests of Normality, Raw Data, Defaulters

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,328	,000	,387	,000
OP to CAB	,085	,006	,786	,000
OP to CAB - TRP	,398	,000	,196	,000
AR to CL	,216	,000	,742	,000
AR to SHE-FA	,173	,000	,810	,000
CA to CL	,316	,000	,485	,000
CA to SHE	,167	,000	,748	,000
CA to TA	,101	,000	,955	,000
CA to TD	,359	,000	,284	,000
CA-CL to SHE	,074	,028	,921	,000
CL to SHE	,206	,000	,721	,000
ΔCAB to TA	,145	,000	,903	,000
FA to SHE	,123	,000	,934	,000
CPR to TRP	,227	,000	,776	,000
CPR to CAB	,325	,000	,503	,000
NWC to TA	,124	,000	,941	,000
ΔSHE to TA	,135	,000	,908	,000
PR to TRP	,148	,000	,887	,000
PR to CAB	,147	,000	,856	,000
TRP to CAB	,190	,000	,768	,000
TRP + OP to CAB	,077	,018	,889	,000
SHE - TL to TL	,292	,000	,491	,000
SHE to TA	,080	,012	,976	,006
Δ(CAB-TRP) to TA(SHE-CAB)	,158	,000	,852	,000
TL to SHE - FA	,184	,000	,783	,000
TL to CAB	,186	,000	,764	,000
TL to TA	,105	,000	,966	,000
ΔVS	,391	,000	,220	,000
V to CA	,270	,000	,468	,000
V to SHE-FA	,207	,000	,726	,000
V to CAB	,204	,000	,730	,000
VS	,308	,000	,498	,000
ΔV	,470	,000	,092	,000
CAB to TA	,074	,027	,969	,001
ΔTRP	,272	,000	,438	,000

Tests of Normality, Raw Data, Non-Defaulters

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,402	,000	,136	,000
OP to CAB	,121	,000	,900	,000
OP to CAB - TRP	,377	,000	,149	,000
AR to CL	,314	,000	,302	,000
AR to SHE-FA	,429	,000	,095	,000
CA to CL	,409	,000	,147	,000
CA to SHE	,186	,000	,728	,000
CA to TA	,084	,000	,829	,000
CA to TD	,388	,000	,172	,000
CA-CL to SHE	,126	,000	,614	,000
CL to SHE	,208	,000	,697	,000
ΔCAB to TA	,363	,000	,057	,000
FA to SHE	,131	,000	,876	,000
CPR to TRP	,383	,000	,254	,000
CPR to CAB	,368	,000	,379	,000
NWC to TA	,047	,000	,897	,000
ΔSHE to TA	,435	,000	,019	,000
PR to TRP	,305	,000	,373	,000
PR to CAB	,157	,000	,808	,000
TRP to CAB	,163	,000	,784	,000
TRP + OP to CAB	,111	,000	,907	,000
SHE - TL to TL	,379	,000	,162	,000
SHE to TA	,082	,000	,956	,000
Δ(CAB-TRP) to TA(SHE-CAB)	,378	,000	,045	,000
TL to SHE - FA	,467	,000	,038	,000
TL to CAB	,197	,000	,714	,000
TL to TA	,083	,000	,860	,000
ΔVS	,440	,000	,113	,000
V to CA	,303	,000	,349	,000
V to SHE-FA	,289	,000	,465	,000
V to CAB	,265	,000	,476	,000
VS	,357	,000	,323	,000
ΔV	,462	,000	,141	,000
CAB to TA	,046	,000	,984	,000
ΔTRP	,434	,000	,048	,000

Tests of Normality, Inverse Transformation, All Data

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,469	,000	,021	,000
OP to CAB	,255	,000	,534	,000
OP to CAB - TRP	,227	,000	,558	,000
AR to CL	,484	,000	,010	,000
AR to SHE-FA	,492	,000	,008	,000
CA to CL	,067	,000	,935	,000
CA to SHE	,153	,000	,648	,000
CA to TA	,232	,000	,522	,000
CA to TD	,067	,000	,923	,000
CA-CL to SHE	,340	,000	,276	,000
CL to SHE	,329	,000	,355	,000
ΔCAB to TA	,449	,000	,036	,000
FA to SHE	,465	,000	,041	,000
CPR to TRP	,504	,000	,014	,000
CPR to CAB	,503	,000	,020	,000
NWC to TA	,312	,000	,371	,000
ΔSHE to TA	,428	,000	,038	,000
PR to TRP	,468	,000	,032	,000
PR to CAB	,369	,000	,197	,000
TRP to CAB	,397	,000	,111	,000
TRP + OP to CAB	,241	,000	,442	,000
SHE - TL to TL	,462	,000	,011	,000
SHE to TA	,202	,000	,692	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,368	,000	,142	,000
TL to SHE - FA	,303	,000	,379	,000
TL to CAB	,308	,000	,379	,000
TL to TA	,312	,000	,382	,000
ΔVS	,465	,000	,012	,000
V to CA	,496	,000	,012	,000
V to SHE-FA	,498	,000	,013	,000
V to CAB	,498	,000	,013	,000
VS	,501	,000	,009	,000
ΔV	,444	,000	,043	,000
CAB to TA	,169	,000	,764	,000
ΔTRP	,252	,000	,286	,000

Tests of Normality, Inverse Transformation, Defaulters

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,366	,000	,312	,000
OP to CAB	,438	,000	,193	,000
OP to CAB - TRP	,204	,000	,612	,000
AR to CL	,392	,000	,246	,000
AR to SHE-FA	,445	,000	,144	,000
CA to CL	,114	,000	,942	,000
CA to SHE	,221	,000	,465	,000
CA to TA	,277	,000	,416	,000
CA to TD	,070	,045	,930	,000
CA-CL to SHE	,361	,000	,348	,000
CL to SHE	,299	,000	,515	,000
ΔCAB to TA	,405	,000	,206	,000
FA to SHE	,355	,000	,329	,000
CPR to TRP	,501	,000	,054	,000
CPR to CAB	,504	,000	,058	,000
NWC to TA	,357	,000	,426	,000
ΔSHE to TA	,279	,000	,562	,000
PR to TRP	,363	,000	,290	,000
PR to CAB	,337	,000	,444	,000
TRP to CAB	,373	,000	,334	,000
TRP + OP to CAB	,439	,000	,154	,000
SHE - TL to TL	,503	,000	,067	,000
SHE to TA	,175	,000	,768	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,294	,000	,475	,000
TL to SHE - FA	,298	,000	,456	,000
TL to CAB	,302	,000	,452	,000
TL to TA	,354	,000	,306	,000
ΔVS	,298	,000	,469	,000
V to CA	,514	,000	,052	,000
V to SHE-FA	,520	,000	,052	,000
V to CAB	,515	,000	,052	,000
VS	,517	,000	,051	,000
ΔV	,432	,000	,096	,000
CAB to TA	,160	,000	,846	,000
ΔTRP	,107	,000	,919	,000

Tests of Normality, Inverse Transformation, Non-Defaulters

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,148	,000	,608	,000
OP to CAB	,059	,000	,981	,000
OP to CAB - TRP	,121	,000	,656	,000
AR to CL	,140	,000	,785	,000
AR to SHE-FA	,092	,000	,803	,000
CA to CL	,241	,000	,555	,000
CA to SHE	,132	,000	,893	,000
CA to TA	,108	,000	,890	,000
CA to TD	,210	,000	,596	,000
CA-CL to SHE	,085	,000	,878	,000
CL to SHE	,116	,000	,914	,000
ΔCAB to TA	,151	,000	,603	,000
FA to SHE	,053	,000	,979	,000
CPR to TRP	,166	,000	,865	,000
CPR to CAB	,226	,000	,729	,000
NWC to TA	,047	,000	,977	,000
ΔSHE to TA	,152	,000	,612	,000
PR to TRP	,233	,000	,720	,000
PR to CAB	,076	,000	,966	,000
TRP to CAB	,089	,000	,942	,000
TRP + OP to CAB	,051	,000	,981	,000
SHE - TL to TL	,168	,000	,677	,000
SHE to TA	,108	,000	,926	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,146	,000	,622	,000
TL to SHE - FA	,124	,000	,758	,000
TL to CAB	,115	,000	,919	,000
TL to TA	,029	,000	,983	,000
ΔVS	,331	,000	,330	,000
V to CA	,095	,000	,854	,000
V to SHE-FA	,095	,000	,865	,000
V to CAB	,080	,000	,890	,000
VS	,151	,000	,758	,000
ΔV	,389	,000	,271	,000
CAB to TA	,059	,000	,977	,000
ΔTRP	,228	,000	,384	,000

Tests of Normality, LN Transformation, All Data

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,058	,000	,963	,000
OP to CAB	,037	,000	,986	,000
OP to CAB - TRP	,024	,001	,983	,000
AR to CL	,168	,000	,841	,000
AR to SHE-FA	,136	,000	,861	,000
CA to CL	,103	,000	,893	,000
CA to SHE	,073	,000	,977	,000
CA to TA	,132	,000	,844	,000
CA to TD	,084	,000	,912	,000
CA-CL to SHE	,116	,000	,872	,000
CL to SHE	,037	,000	,991	,000
ΔCAB to TA	,111	,000	,848	,000
FA to SHE	,069	,000	,938	,000
CPR to TRP	,142	,000	,888	,000
CPR to CAB	,098	,000	,950	,000
NWC to TA	,092	,000	,934	,000
ΔSHE to TA	,112	,000	,846	,000
PR to TRP	,259	,000	,661	,000
PR to CAB	,061	,000	,970	,000
TRP to CAB	,027	,000	,987	,000
TRP + OP to CAB	,024	,000	,992	,000
SHE - TL to TL	,065	,000	,951	,000
SHE to TA	,137	,000	,877	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,114	,000	,830	,000
TL to SHE - FA	,018	,032	,997	,000
TL to CAB	,026	,000	,995	,000
TL to TA	,076	,000	,936	,000
ΔVS	,190	,000	,747	,000
V to CA	,105	,000	,878	,000
V to SHE-FA	,104	,000	,886	,000
V to CAB	,107	,000	,874	,000
VS	,030	,000	,969	,000
ΔV	,254	,000	,595	,000
CAB to TA	,094	,000	,944	,000
ΔTRP	,105	,000	,894	,000

Tests of Normality, LN Transformation, Defaulters

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,113	,000	,958	,000
OP to CAB	,080	,013	,950	,000
OP to CAB - TRP	,104	,000	,936	,000
AR to CL	,188	,000	,853	,000
AR to SHE-FA	,160	,000	,866	,000
CA to CL	,147	,000	,846	,000
CA to SHE	,056	,200*	,980	,016
CA to TA	,158	,000	,807	,000
CA to TD	,152	,000	,876	,000
CA-CL to SHE	,129	,000	,920	,000
CL to SHE	,055	,200*	,981	,020
ΔCAB to TA	,168	,000	,843	,000
FA to SHE	,089	,003	,912	,000
CPR to TRP	,171	,000	,842	,000
CPR to CAB	,104	,000	,935	,000
NWC to TA	,084	,006	,971	,001
ΔSHE to TA	,158	,000	,854	,000
PR to TRP	,208	,000	,776	,000
PR to CAB	,053	,200*	,990	,272
TRP to CAB	,055	,200*	,991	,361
TRP + OP to CAB	,067	,070	,983	,037
SHE - TL to TL	,101	,000	,931	,000
SHE to TA	,111	,000	,921	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,190	,000	,737	,000
TL to SHE - FA	,065	,085	,985	,084
TL to CAB	,057	,200*	,986	,097
TL to TA	,113	,000	,893	,000
ΔVS	,138	,000	,863	,000
V to CA	,184	,000	,796	,000
V to SHE-FA	,151	,000	,831	,000
V to CAB	,163	,000	,817	,000
VS	,111	,000	,897	,000
ΔV	,237	,000	,662	,000
CAB to TA	,065	,083	,966	,001
ΔTRP	,089	,003	,952	,000

Tests of Normality, LN Transformation, Non-Defaulters

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,057	,000	,960	,000
OP to CAB	,038	,000	,985	,000
OP to CAB - TRP	,024	,001	,988	,000
AR to CL	,168	,000	,839	,000
AR to SHE-FA	,137	,000	,860	,000
CA to CL	,101	,000	,894	,000
CA to SHE	,074	,000	,977	,000
CA to TA	,132	,000	,847	,000
CA to TD	,083	,000	,912	,000
CA-CL to SHE	,115	,000	,869	,000
CL to SHE	,038	,000	,991	,000
ΔCAB to TA	,105	,000	,847	,000
FA to SHE	,068	,000	,939	,000
CPR to TRP	,141	,000	,890	,000
CPR to CAB	,100	,000	,951	,000
NWC to TA	,094	,000	,932	,000
ΔSHE to TA	,106	,000	,847	,000
PR to TRP	,262	,000	,654	,000
PR to CAB	,063	,000	,968	,000
TRP to CAB	,030	,000	,985	,000
TRP + OP to CAB	,026	,000	,991	,000
SHE - TL to TL	,067	,000	,952	,000
SHE to TA	,139	,000	,874	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,105	,000	,845	,000
TL to SHE - FA	,018	,029	,996	,000
TL to CAB	,025	,000	,995	,000
TL to TA	,078	,000	,938	,000
ΔVS	,194	,000	,741	,000
V to CA	,102	,000	,885	,000
V to SHE-FA	,101	,000	,890	,000
V to CAB	,104	,000	,879	,000
VS	,025	,000	,974	,000
ΔV	,258	,000	,591	,000
CAB to TA	,098	,000	,941	,000
ΔTRP	,106	,000	,888	,000

Tests of Normality, Square Root Transformation, All Data

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,144	,000	,622	,000
OP to CAB	,058	,000	,978	,000
OP to CAB - TRP	,143	,000	,591	,000
AR to CL	,140	,000	,787	,000
AR to SHE-FA	,089	,000	,812	,000
CA to CL	,241	,000	,560	,000
CA to SHE	,131	,000	,894	,000
CA to TA	,107	,000	,892	,000
CA to TD	,211	,000	,598	,000
CA-CL to SHE	,083	,000	,884	,000
CL to SHE	,115	,000	,914	,000
ΔCAB to TA	,151	,000	,623	,000
FA to SHE	,051	,000	,980	,000
CPR to TRP	,164	,000	,867	,000
CPR to CAB	,226	,000	,731	,000
NWC to TA	,046	,000	,978	,000
ΔSHE to TA	,151	,000	,633	,000
PR to TRP	,230	,000	,728	,000
PR to CAB	,075	,000	,967	,000
TRP to CAB	,089	,000	,940	,000
TRP + OP to CAB	,054	,000	,980	,000
SHE - TL to TL	,168	,000	,681	,000
SHE to TA	,107	,000	,928	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,146	,000	,638	,000
TL to SHE - FA	,122	,000	,770	,000
TL to CAB	,113	,000	,920	,000
TL to TA	,030	,000	,984	,000
ΔVS	,330	,000	,331	,000
V to CA	,095	,000	,857	,000
V to SHE-FA	,093	,000	,873	,000
V to CAB	,078	,000	,896	,000
VS	,152	,000	,756	,000
ΔV	,388	,000	,269	,000
CAB to TA	,055	,000	,978	,000
ΔTRP	,224	,000	,395	,000

Tests of Normality, Square Root Transformation, Defaulters

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,179	,000	,785	,000
OP to CAB	,040	,200*	,960	,000
OP to CAB - TRP	,264	,000	,492	,000
AR to CL	,127	,000	,921	,000
AR to SHE-FA	,059	,200*	,969	,001
CA to CL	,248	,000	,680	,000
CA to SHE	,112	,000	,916	,000
CA to TA	,130	,000	,905	,000
CA to TD	,247	,000	,601	,000
CA-CL to SHE	,087	,004	,957	,000
CL to SHE	,090	,002	,932	,000
ΔCAB to TA	,156	,000	,877	,000
FA to SHE	,060	,200*	,988	,196
CPR to TRP	,151	,000	,886	,000
CPR to CAB	,209	,000	,786	,000
NWC to TA	,069	,056	,985	,082
ΔSHE to TA	,146	,000	,884	,000
PR to TRP	,170	,000	,864	,000
PR to CAB	,068	,058	,976	,006
TRP to CAB	,106	,000	,948	,000
TRP + OP to CAB	,032	,200*	,984	,062
SHE - TL to TL	,174	,000	,754	,000
SHE to TA	,099	,000	,960	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,174	,000	,801	,000
TL to SHE - FA	,090	,002	,945	,000
TL to CAB	,086	,004	,944	,000
TL to TA	,071	,040	,975	,004
ΔVS	,254	,000	,521	,000
V to CA	,114	,000	,891	,000
V to SHE-FA	,066	,078	,958	,000
V to CAB	,059	,200*	,963	,000
VS	,142	,000	,829	,000
ΔV	,376	,000	,233	,000
CAB to TA	,047	,200*	,982	,030
ΔTRP	,183	,000	,735	,000

Tests of Normality, Square Root Transformation, Non-Defaulters

	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
LTL to SHE	,469	,000	,021	,000
OP to CAB	,238	,000	,578	,000
OP to CAB - TRP	,228	,000	,559	,000
AR to CL	,484	,000	,011	,000
AR to SHE-FA	,493	,000	,009	,000
CA to CL	,068	,000	,933	,000
CA to SHE	,148	,000	,678	,000
CA to TA	,225	,000	,542	,000
CA to TD	,069	,000	,923	,000
CA-CL to SHE	,334	,000	,271	,000
CL to SHE	,330	,000	,351	,000
ΔCAB to TA	,450	,000	,035	,000
FA to SHE	,465	,000	,042	,000
CPR to TRP	,505	,000	,015	,000
CPR to CAB	,503	,000	,021	,000
NWC to TA	,303	,000	,369	,000
ΔSHE to TA	,429	,000	,038	,000
PR to TRP	,468	,000	,032	,000
PR to CAB	,369	,000	,193	,000
TRP to CAB	,398	,000	,106	,000
TRP + OP to CAB	,212	,000	,514	,000
SHE - TL to TL	,330	,000	,286	,000
SHE to TA	,204	,000	,686	,000
Δ(CAB-TRP) to TA-(SHE-CAB)	,370	,000	,141	,000
TL to SHE - FA	,303	,000	,376	,000
TL to CAB	,309	,000	,376	,000
TL to TA	,310	,000	,388	,000
ΔVS	,465	,000	,012	,000
V to CA	,495	,000	,010	,000
V to SHE-FA	,496	,000	,010	,000
V to CAB	,496	,000	,010	,000
VS	,500	,000	,014	,000
ΔV	,445	,000	,042	,000
CAB to TA	,172	,000	,758	,000
ΔTRP	,260	,000	,274	,000

APPENDIX C: GROUP STATISTICS

Variable	Defaulters Mean	Defaulters Std. Deviation	Defaulters Valid N	Non-Defaulters Mean	Non-Defaulters Std. Deviation	Non-Defaulters Valid N	All Mean	All Std. Deviation	All Valid N
LTL to SHE	,092	,152	136	,063	,256	2876	,065	,252	3012
OP to CAB	,476	,317	136	,258	,184	2876	,268	,197	3012
OP to CAB - TRP	1,607	5,910	136	,420	1,303	2876	,474	1,803	3012
AR to CL	1,183	1,274	136	1,793	3,804	2876	1,765	3,729	3012
AR to SHE-FA	1,298	1,355	136	,969	6,292	2876	,984	6,156	3012
CA to CL	4,583	8,031	136	6,501	23,955	2876	6,414	23,473	3012
CA to SHE	1,537	1,193	136	1,305	,899	2876	1,316	,915	3012
CA to TA	,680	,169	136	,717	,185	2876	,715	,184	3012
CA to TD	5,088	13,308	136	5,160	15,567	2876	5,157	15,471	3012
CA-CL to SHE	,504	,282	136	,623	,339	2876	,618	,338	3012
CL to SHE	1,033	1,198	136	,682	,835	2876	,698	,858	3012
ΔCAB to TA	-,021	,151	136	,056	,783	2876	,052	,766	3012
FA to SHE	,273	,195	136	,217	,190	2876	,220	,191	3012
CPR to TRP	,171	,216	136	,117	,400	2876	,119	,394	3012
CPR to CAB	,056	,123	136	,029	,088	2876	,030	,090	3012
NWC to TA	,311	,212	136	,416	,223	2876	,411	,224	3012
ΔSHE to TA	-,008	,177	136	,047	2,010	2876	,044	1,965	3012
PR to TRP	,728	,252	136	,788	,423	2876	,785	,417	3012
PR to CAB	,152	,123	136	,112	,095	2876	,114	,097	3012
TRP to CAB	,247	,241	136	,163	,145	2876	,167	,152	3012
TRP + OP to CAB	,722	,434	136	,420	,265	2876	,434	,282	3012
SHE - TL to TL	3,550	8,730	136	4,485	17,400	2876	4,443	17,104	3012
SHE to TA	,586	,206	136	,669	,198	2876	,665	,199	3012
Δ(CAB-TRP) to TA-(SHE-	-,029	,157	136	,050	1,095	2876	,047	1,071	3012
TL to SHE - FA	1,411	1,592	136	,785	11,594	2876	,813	11,335	3012
TL to CAB	1,332	1,481	136	,885	1,026	2876	,905	1,055	3012
TL to TA	,378	,215	136	,313	,208	2876	,315	,209	3012
ΔVS	2,890	16,560	136	10,612	77,141	2876	10,264	75,477	3012
V to CA	68,614	114,395	136	59,625	115,588	2876	60,031	115,530	3012
V to SHE-FA	128,237	157,163	136	89,812	165,035	2876	91,547	164,856	3012
V to CAB	116,310	138,203	136	84,071	133,900	2876	85,526	134,241	3012
VS	,004	,007	136	,009	,025	2876	,009	,025	3012
ΔV	14,769	124,670	136	17,091	111,387	2876	16,986	111,999	3012
CAB to TA	,444	,191	136	,537	,206	2876	,533	,206	3012
ΔTRP	1,450	1,605	136	2,035	11,938	2876	2,008	11,671	3012
Prev Def	-,382	,927	136	,285	,959	2876	,255	,967	3012

APPENDIX D : COVARIANCE AND CORRELATION MATRICES

Correlation (ALL)	LTLtoSHE	OPtoCAB	OPtoCAB-TRP	ARtoCL	ARtoSHE-FA	CAtoCL	CAtoSHE	CAtoTA	CAtoTD	CA-CLtoSHE	CLtoSHE	CABtoTA	FAtoSHE	CPRtoTRP	CPRtoCAB	NWCtoTA	SHEtoTA	PRtoTRP	PRtoCAB	TRPtoCAB	TRP+OPtoCAB	SHE-TLtoTL	SHEtoTA	CAB-TRPtoTA-(SHE-CAB)	TLtoSHE-FA	TLtoCAB	TLtoTA	VSc	VtoCA	VtoSHE-FA	VtoCAB	VS	Vc	CABtoTA	TRPc	PrevDef
LTLtoSHE	1	,11	,05	-,01	,02	,03	,32	,04	-,04	,66	,09	-,01	,04	-,57	-,20	,03	,00	,53	,34	,14	,15	-,05	-,22	,00	,05	,41	,21	-,01	,00	,09	,09	,05	-,01	-,18	-,01	-,04
OPtoCAB	,11	1	,24	-,11	,08	-,14	,18	-,04	-,17	-,12	,24	-,05	,31	-,01	,05	-,34	-,04	,01	,32	,27	,85	-,17	-,38	-,04	,06	,38	,34	-,01	,14	,27	,29	-,01	,07	-,44	,03	-,21
OPtoCAB-TRP	,05	,24	1	-,03	,03	-,03	,14	-,01	-,04	-,05	,16	-,01	,13	,04	,22	-,14	-,01	-,06	,26	,37	,37	-,04	-,16	-,01	,02	,24	,15	,00	,02	,09	,08	,03	,00	-,17	,03	-,03
ARtoCL	-,01	-,11	-,03	1	,01	,15	-,07	,12	,12	,14	-,13	,00	,00	-,05	-,07	,30	,00	,04	-,08	-,10	-,13	,15	,22	,01	,00	-,09	-,08	,01	-,05	-,08	-,08	-,04	-,01	,16	-,01	,02
ARtoSHE-FA	,02	,08	,03	,01	1	-,02	,12	,04	,01	,00	,13	-,01	,05	-,01	-,02	-,06	,00	,01	,10	,06	,09	-,02	-,11	-,01	,90	,09	,07	-,01	-,01	,02	,03	,00	,00	-,12	,00	-,03
CAtoCL	,03	-,14	-,03	,15	-,02	1	-,07	,09	,64	,15	-,13	,02	-,11	,01	,02	,28	,01	-,01	-,15	-,10	-,15	,71	,21	,01	-,01	-,11	-,16	,02	-,05	-,07	-,08	-,02	-,01	,24	,00	,02
CAtoSHE	,32	,18	,14	-,07	,12	-,07	1	,55	,09	,35	,93	,00	-,13	-,20	-,07	-,23	,00	,17	,60	,43	,36	-,12	-,80	-,01	,06	,70	,57	-,01	-,11	,08	,11	-,02	,00	-,55	,01	-,15
CAtoTA	,04	-,04	-,01	,12	,04	,09	,55	1	,11	,65	,33	,03	-,46	-,01	-,02	,54	,01	-,01	,04	,04	-,01	-,02	-,30	,02	,02	,22	,37	,01	-,17	-,05	-,03	-,06	,03	,07	,02	-,06
CAtoTD	-,04	-,17	-,04	,12	,01	,64	,09	,11	1	,09	,06	,01	-,12	,02	,01	,17	,00	-,02	-,09	-,06	-,15	,91	,11	,01	-,01	-,17	-,26	,02	-,06	-,09	-,09	-,04	,00	,16	,00	-,02
CA-CLtoSHE	,66	-,12	-,05	,14	,00	,15	,35	,65	,09	1	-,02	,03	-,35	-,41	-,18	,64	,01	,36	-,01	-,12	-,15	,04	-,01	,02	,02	,13	,09	,00	-,12	-,07	-,06	,00	,02	,21	,01	,01
CLtoSHE	,09	,24	,16	-,13	,13	-,13	,93	,33	,06	-,02	1	-,02	,00	-,05	-,01	-,50	,00	,04	,64	,51	,45	-,14	-,86	-,01	,06	,69	,57	-,01	-,07	,12	,13	-,02	-,01	-,67	,01	-,17
CABtoTA	-,01	-,05	-,01	,00	-,01	,02	,00	,03	,01	,03	-,02	1	-,08	,01	,00	,04	,99	-,02	-,04	-,03	-,05	,01	,02	,99	,00	-,03	-,01	-,04	,01	,00	,00	,01	,02	,07	,01	,00
FAtoSHE	,04	,31	,13	,00	,05	-,11	-,13	-,46	-,12	-,35	,00	-,08	1	-,08	,00	-,42	-,04	,07	,35	,26	,36	-,06	-,06	-,07	-,01	,24	,06	-,02	,02	,18	,12	,02	-,01	-,60	,00	-,02
CPRtoTRP	-,57	-,01	,04	-,05	-,01	,01	-,20	-,01	,02	-,41	-,05	,01	-,08	1	,60	,02	,00	-,92	-,31	,14	,07	,03	,13	,00	-,03	-,26	-,11	,00	,02	-,05	-,04	-,05	,00	,14	,03	,02
CPRtoCAB	-,20	,05	,22	-,07	-,02	,02	-,07	-,02	,01	-,18	-,01	,00	,00	,60	1	-,03	,00	-,54	-,05	,56	,34	,02	,02	-,02	-,01	-,04	,00	,00	,02	,01	,01	,00	-,01	,04	,06	-,01
NWCtoTA	,03	-,34	-,14	,30	-,06	,28	-,23	,54	,17	,64	-,50	,04	-,42	,02	-,03	1	,02	-,03	-,54	-,42	-,46	,21	,60	,03	-,03	-,44	-,35	,02	-,10	-,19	-,19	-,03	,02	,74	,02	,12
SHEtoTA	,00	-,04	-,01	,00	,00	,01	,00	,01	,00	,01	,00	,99	-,04	,00	,00	,02	1	-,01	-,02	-,01	-,03	,01	,01	,99	,00	-,01	,00	-,05	,01	,00	,00	,00	,01	,03	,00	-,01
PRtoTRP	,53	,01	-,06	,04	,01	-,01	,17	-,01	-,02	,36	,04	-,02	,07	-,92	-,54	-,03	-,01	1	,30	-,22	-,12	-,03	-,12	,00	,03	,24	,10	,01	-,01	,04	,03	,06	,01	-,12	-,05	,00
PRtoCAB	,34	,32	,26	-,08	,10	-,15	,60	,04	-,09	-,01	,64	-,04	,35	-,31	-,05	-,54	-,02	,30	1	,70	,61	-,16	-,70	-,04	,04	,76	,57	-,03	-,02	,22	,20	,03	-,02	-,70	,00	-,19
TRPtoCAB	,14	,27	,37	-,10	,06	-,10	,43	,04	-,06	-,12	,51	-,03	,26	,14	,56	-,42	-,01	-,22	,70	1	,74	-,11	-,53	-,04	,02	,58	,44	-,01	-,01	,17	,15	,02	-,01	-,52	,08	-,14
TRP+OPtoCAB	,15	,85	,37	-,13	,09	-,15	,36	-,01	-,15	-,15	,45	-,05	,36	,07	,34	-,46	-,03	-,12	,61	,74	1	-,18	-,55	-,05	,05	,58	,48	-,01	,09	,28	,28	,00	,04	-,59	,06	-,22
SHE-TLtoTL	-,05	-,17	-,04	,15	-,02	,71	-,12	-,02	,91	,04	-,14	,01	-,06	,03	,02	,21	,01	-,03	-,16	-,11	-,18	1	,27	,01	-,01	-,18	-,27	,02	-,04	-,08	-,09	-,03	,00	,25	,00	,03
SHEtoTA	-,22	-,38	-,16	,22	-,11	,21	-,80	-,30	,11	-,01	-,86	,02	-,06	,13	,02	,60	,01	-,12	-,70	-,53	-,55	,27	1	,02	-,06	-,77	-,78	,02	,04	-,19	-,21	,02	,00	,81	,00	,19
CAB-TRPtoTA-(SHE-CAB)	,00	-,04	-,01	,01	-,01	,01	-,01	,02	,01	,02	-,01	,99	-,07	,00	-,02	,03	,99	,00	-,04	-,04	-,05	,01	,02	1	,00	-,03	-,01	-,04	,01	,00	-,01	,00	,01	,06	,00	-,01
TLtoSHE-FA	,05	,06	,02	,00	,90	-,01	,06	,02	-,01	,02	,06	,00	-,01	-,03	-,01	-,03	,00	,03	,04	,02	,05	-,01	-,06	,00	1	,08	,06	,00	,00	,00	,02	,01	,00	-,05	,00	-,03
TLtoCAB	,41	,38	,24	-,09	,09	-,11	,70	,22	-,17	,13	,69	-,03	,24	-,26	-,04	-,44	-,01	,24	,76	,58	,58	-,18	-,77	-,03	,08	1	,82	-,02	-,04	,22	,23	,03	-,01	-,70	,01	-,17
TLtoTA	,21	,34	,15	-,08	,07	-,16	,57	,37	-,26	,09	,57	-,01	,06	-,11	,00	-,35	,00	,10	,57	,44	,48	-,27	-,78	-,01	,06	,82	1	-,02	-,01	,20	,22	,01	,01	-,62	,01	-,15
VSc	-,01	-,01	,00	,01	-,01	,02	-,01	,01	,02	,00	-,01	-,04	-,02	,00	,00	,02	-,05	,01	-,03	-,01	-,01	,02	,02	-,04	,00	-,02	-,02	1	,01	,00	,00	,08	,54	,03	,01	,02
VtoCA	,00	,14	,02	-,05	-,01	-,05	-,11	-,17	-,06	-,12	-,07	,01	,02	,02	,02	-,10	,01	-,01	-,02	-,01	,09	-,04	,04	,01	,00	-,04	-,01	,01	1	,72	,85	,48	,04	,02	,00	-,05
VtoSHE-FA	,09	,27	,09	-,08	,02	-,07	,08	-,05	-,09	-,07	,12	,00	,18	-,05	,01	-,19	,00	,04	,22	,17	,28	-,08	-,19	,00	,00	,22	,20	,00	,72	1	,86	,34	,05	-,22	,00	-,11
VtoCAB	,09	,29	,08	-,08	,03	-,08	,11	-,03	-,09	-,06	,13	,00	,12	-,04	,01	-,19	,00	,03	,20	,15	,28	-,09	-,21	-,01	,02	,23	,22	,00	,85	,86	1	,41	,06	-,22	,00	-,13
VS	,05	-,01	,03	-,04	,00	-,02	-,02	-,06	-,04	,00	-,02	,01	,02	-,05	,00	-,03	,00	,06	,03	,02	,00	-,03	,02	,00	,01	,03	,01	,08	,48	,34	,41	1	,11	,01	-,01	,03
Vc	-,01	,07	,00	-,01	,00	-,01	,00	,03	,00	,02	-,01	,02	-,01	,00	-,01	,02	,01	,01	-,02	-,01	,04	,00	,00	,01	,00	-,01	,01	,54	,04	,05	,06	,11	1	,01	,03	,04
CABtoTA	-,18	-,44	-,17	,16	-,12	,24	-,55	,07	,16	,21	-,67	,07	-,60	,14	,04	,74	,03	-,12	-,70	-,52	-,59	,25	,81	,06	-,05	-,70	-,62	,03	,02	-,22	-,22	,01	,01	1	,00	,14
TRPc	-,01	,03	,03	-,01	,00	,00	,01	,02	,00	,01	,01	,01	,00	,03	,06	,02	,00	-,05	,00	,08	,06	,00	,00	,00	,00	,01	,01	,01	,00	,00	,00	-,01	,03	,00	1	,01
PrevDef	-,04	-,21	-,03	,02	-,03	,02	-,15	-,06	-,02	,01	-,17	,00	-,02	,02	-,01	,12	-,01	,00	-,19	-,14	-,22	,03	,19	-,01	-,03	-,17	-,15	,02	-,05	-,11	-,13	,03	,04	,14	,01	1

Covariance (Defaulters)	LTLtoSHE	OPtoCAB	OPtoCAB-TRP	ARtoCL	ARtoSHE-FA	CAtoCL	CAtoSHE	CAtoTA	CAtoTD	CA-CLtoSHE	CLtoSHE	CABtoTA	FAtoSHE	CPRtoTRP	CPRtoCAB	NWCtoTA	SHEtoTA	PRtoTRP	PRtoCAB	TRPtoCAB	TRP+OPtoCAB	SHE-TLtoTL	SHEtoTA	CAB-TRPtoTA-(SHE-CAB)	TLtoSHE-FA	TLtoCAB	TLtoTA	VSc	VtoCA	VtoSHE-FA	VtoCAB	VS	Vc	CABtoTA	TRPc	PrevDef
LTLtoSHE	,02	,00	,11	,03	,01	-,04	,01	,00	-,20	,00	,01	,00	,00	,00	,00	,00	,00	,00	,00	,01	,01	-,20	-,01	,00	,04	,04	,01	-,10	-,45	-,06	,17	,00	-,62	,00	-,02	,00
OPtoCAB	,00	,10	,35	-,01	,08	-,61	,00	-,01	-,93	-,01	,02	-,01	,01	,02	,00	-,02	-,01	-,01	,01	,01	,12	-,60	-,01	-,01	,13	,12	,02	-,44	3,32	14,26	11,00	,00	,12	-,02	-,02	-,02
OPtoCAB-TRP	,11	,35	34,93	-,32	1,44	-3,91	-,11	-,12	-5,11	-,27	,16	-,02	,34	,25	,30	-,22	-,02	-,31	,19	,63	,98	-4,34	-,14	-,10	2,48	1,40	,18	-3,48	-7,91	90,16	36,22	,02	-15,25	-,23	-,50	,55
ARtoCL	,03	-,01	-,32	1,62	-,01	,57	-,15	,00	-,11	,07	-,23	-,01	-,02	,01	-,01	,07	,00	,02	-,02	-,04	-,05	,60	,05	,01	-,24	-,26	-,04	-1,98	4,81	-,47	-4,55	,00	-4,57	,05	,04	,03
ARtoSHE-FA	,01	,08	1,44	-,01	1,84	-3,54	1,08	,08	1,27	,00	1,08	,00	,05	-,06	-,01	-,13	,01	,08	,12	,11	,19	-2,72	-,20	,00	1,46	1,32	,15	-1,73	10,75	96,95	82,56	,00	-7,41	-,18	-,17	-,12
CAtoCL	-,04	-,61	-3,91	,57	-3,54	64,50	-2,08	,18	41,41	,83	-2,90	-,34	-,40	,14	-,08	1,09	-,38	-,17	-,34	-,47	-1,08	56,37	,87	-,29	-3,71	-3,46	-,79	43,49	-135,05	-305,95	-276,86	-,01	4,35	,96	1,30	-,69
CAtoSHE	,01	,00	-,11	-,15	1,08	-2,08	1,42	,12	2,07	,03	1,39	,01	-,04	-,08	-,02	-,08	,01	,06	,08	,13	,13	-1,81	-,19	,01	1,38	1,36	,15	-,94	-7,25	45,73	49,70	,00	-3,06	-,13	-,24	-,14
CAtoTA	,00	-,01	-,12	,00	,08	,18	,12	,03	,42	,03	,09	,00	-,02	-,01	-,01	,01	,00	,01	,00	,00	-,01	,01	-,01	,00	,08	,08	,01	,14	-4,36	,50	1,28	,00	1,54	,00	,01	-,02
CAtoTD	-,20	-,93	-5,11	-,11	1,27	41,41	2,07	,42	177,11	,73	1,35	-,26	-,47	-,11	-,14	,49	-,29	-,05	-,15	-,29	-1,22	80,79	,15	-,22	-4,77	-4,46	-1,14	3,01	-69,13	-292,28	-256,51	-,01	63,20	,33	-,63	-1,03
CA-CLtoSHE	,00	-,01	-,27	,07	,00	,83	,03	,03	,73	,08	-,05	,00	-,03	-,01	-,01	,05	,00	,01	-,01	-,02	-,04	,48	,01	,00	-,06	-,04	-,01	,37	-6,44	-6,03	-4,78	,00	2,66	,02	,04	-,01
CLtoSHE	,01	,02	,16	-,23	1,08	-2,90	1,39	,09	1,35	-,05	1,44	,01	-,01	-,06	-,01	-,12	,01	,05	,09	,15	,17	-2,30	-,20	,00	1,44	1,40	,16	-1,31	-,81	51,76	54,48	,00	-5,71	-,15	-,28	-,14
CABtoTA	,00	-,01	-,02	-,01	,00	-,34	,01	,00	-,26	,00	,01	,02	,00	,00	,00	,00	,02	,00	,00	,00	-,01	-,37	,00	,02	,00	,01	,00	,04	,83	1,39	,98	,00	,77	,00	-,02	-,02
FAtoSHE	,00	,01	,34	-,02	,05	-,40	-,04	-,02	-,47	-,03	-,01	,00	,04	,00	,00	-,02	,00	-,01	,01	,01	,02	-,20	,00	,00	,04	,03	,00	-,32	2,10	8,45	4,81	,00	-1,71	-,02	,00	,02
CPRtoTRP	,00	,02	,25	,01	-,06	,14	-,08	-,01	-,11	-,01	-,06	,00	,00	,05	,02	-,01	,00	-,04	,00	,01	,03	,17	,01	,00	-,04	-,05	,00	-,28	,97	-1,64	-2,07	,00	1,61	,00	-,01	,01
CPRtoCAB	,00	,00	,30	-,01	-,01	-,08	-,02	-,01	-,14	-,01	-,01	,00	,00	,02	,02	-,01	,00	-,02	,00	,02	,02	-,08	,00	,00	,01	,00	,00	-,11	,36	,76	,20	,00	,05	,00	-,01	,01
NWCtoTA	,00	-,02	-,22	,07	-,13	1,09	-,08	,01	,49	,05	-,12	,00	-,02	-,01	-,01	,04	,00	,00	-,02	-,03	-,05	,77	,03	,00	-,16	-,15	-,03	,55	-4,23	-9,94	-9,22	,00	1,74	,03	,05	-,01
SHEtoTA	,00	-,01	-,02	,00	,01	-,38	,01	,00	-,29	,00	,01	,02	,00	,00	,00	,00	,03	,00	,00	,00	-,01	-,35	,00	,02	,01	,00	,00	,06	1,03	3,30	1,91	,00	1,00	,00	-,01	-,03
PRtoTRP	,00	-,01	-,31	,02	,08	-,17	,06	,01	-,05	,01	,05	,00	-,01	-,04	-,02	,00	,00	,06	,01	-,02	-,03	-,37	-,01	,00	,04	,04	,01	,48	1,14	4,83	4,51	,00	-,65	,00	,03	-,01
PRtoCAB	,00	,01	,19	-,02	,12	-,34	,08	,00	-,15	-,01	,09	,00	,01	,00	,00	-,02	,00	,01	,02	,02	,03	-,33	-,02	,00	,15	,14	,02	-,09	,61	7,29	6,58	,00	-,52	-,02	-,03	-,01
TRPtoCAB	,01	,01	,63	-,04	,11	-,47	,13	,00	-,29	-,02	,15	,00	,01	,01	,02	-,03	,00	-,02	,02	,06	,07	-,46	-,03	-,01	,25	,22	,03	-,29	-,29	7,77	6,62	,00	-,92	-,02	-,06	,00
TRP+OPtoCAB	,01	,12	,98	-,05	,19	-1,08	,13	-,01	-1,22	-,04	,17	-,01	,02	,03	,02	-,05	-,01	-,03	,03	,07	,19	-1,06	-,04	-,02	,38	,34	,04	-,74	3,03	22,03	17,61	,00	-,80	-,04	-,08	-,01
SHE-TLtoTL	-,20	-,60	-4,34	,60	-2,72	56,37	-1,81	,01	80,79	,48	-2,30	-,37	-,20	,17	-,08	,77	-,35	-,37	-,33	-,46	-1,06	76,21	,82	-,32	-4,58	-4,28	-1,01	6,04	-94,73	-305,60	-280,26	-,01	41,27	,75	-,20	-,64
SHEtoTA	-,01	-,01	-,14	,05	-,20	,87	-,19	-,01	,15	,01	-,20	,00	,00	,01	,00	,03	,00	-,01	-,02	-,03	-,04	,82	,04	,00	-,24	-,22	-,04	,40	,26	-9,65	-9,88	,00	,41	,03	,05	,01
CAB-TRPtoTA-(SHE-CAB)	,00	-,01	-,10	,01	,00	-,29	,01	,00	-,22	,00	,00	,02	,00	,00	,00	,00	,02	,00	,00	-,01	-,02	-,32	,00	,02	-,01	-,01	,00	,08	2,27	2,48	1,96	,00	1,98	,00	-,01	-,02
TLtoSHE-FA	,04	,13	2,48	-,24	1,46	-3,71	1,38	,08	-4,77	-,06	1,44	,00	,04	-,04	,01	-,16	,01	,04	,15	,25	,38	-4,58	-,24	-,01	2,53	2,31	,27	-1,37	-2,04	104,26	94,07	,00	-15,56	-,20	-,25	-,20
TLtoCAB	,04	,12	1,40	-,26	1,32	-3,46	1,36	,08	-4,46	-,04	1,40	,01	,03	-,05	,00	-,15	,00	,04	,14	,22	,34	-4,28	-,22	-,01	2,31	2,19	,26	-1,41	-4,34	87,30	85,68	,00	-14,61	-,19	-,26	-,16
TLtoTA	,01	,02	,18	-,04	,15	-,79	,15	,01	-1,14	-,01	,16	,00	,00	,00	,00	-,03	,00	,01	,02	,03	,04	-1,01	-,04	,00	,27	,26	,05	-,34	,17	11,86	11,70	,00	-3,74	-,03	-,04	-,02
VSc	-,10	-,44	-3,48	-1,98	-1,73	43,49	-,94	,14	3,01	,37	-1,31	,04	-,32	-,28	-,11	,55	,06	,48	-,09	-,29	-,74	6,04	,40	,08	-1,37	-1,41	-,34	274,22	-36,60	-106,74	-101,89	-,01	170,76	,57	-1,53	-,91
VtoCA	-,45	3,32	-7,91	4,81	10,75	-135,05	-7,25	-4,36	-69,13	-6,44	-,81	,83	2,10	,97	,36	-4,23	1,03	1,14	,61	-,29	3,03	-94,73	,26	2,27	-2,04	-4,34	,17	-36,60	13086,20	13218,51	12308,48	,22	-410,57	-,94	-4,94	,15
VtoSHE-FA	-,06	14,26	90,16	-,47	96,95	-305,95	45,73	,50	-292,28	-6,03	51,76	1,39	8,45	-1,64	,76	-9,94	3,30	4,83	7,29	7,77	22,03	-305,60	-9,65	2,48	104,26	87,30	11,86	-106,74	13218,51	24700,25	20412,51	,48	-823,30	-11,03	10,43	-14,29
VtoCAB	,17	11,00	36,22	-4,55	82,56	-276,86	49,70	1,28	-256,51	-4,78	54,48	,98	4,81	-2,07	,20	-9,22	1,91	4,51	6,58	6,62	17,61	-280,26	-9,88	1,96	94,07	85,68	11,70	-101,89	12308,48	20412,51	19100,13	,40	-660,89	-10,07	-12,08	-12,71
VS	,00	,00	,02	,00	,00	-,01	,00	,00	-,01	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	-,01	,00	,00	,00	,00	,00	-,01	,22	,48	,40	,00	-,05	,00	,00	,00
Vc	-,62	,12	-15,25	-4,57	-7,41	4,35	-3,06	1,54	63,20	2,66	-5,71	,77	-1,71	1,61	,05	1,74	1,00	-,65	-,52	-,92	-,80	41,27	,41	1,98	-15,56	-14,61	-3,74	170,76	-410,57	-823,30	-660,89	-,05	15542,53	1,26	-9,03	-4,56
CABtoTA	,00	-,02	-,23	,05	-,18	,96	-,13	,00	,33	,02	-,15	,00	-,02	,00	,00	,03	,00	-,01	-,02	-,02	-,04	,75	,03	,00	-,20	-,19	-,03	,57	-,94	-11,03	-10,07	,00	1,26	,04	,04	,00
TRPc	-,02	-,02	-,50	,04	-,17	1,30	-,24	,01	-,63	,04	-,28	-,02	,00	-,01	-,01	,05	-,01	,03	-,03	-,06	-,08	-,20	,05	-,01	-,25	-,26	-,04	-1,53	-4,94	10,43	-12,08	,00	-9,03	,04	2,57	-,02
PrevDef	,00	-,02	,55	,03	-,12	-,69	-,14	-,02	-1,03	-,01	-,14	-,02	,02	,01	,01	-,01	-,03	-,01	-,01	,00	-,01	-,64	,01	-,02	-,20	-,16	-,02	-,91	,15	-14,29	-12,71	,00	-4,56	,00	-,02	,86

Covariance (Non-Defaulters)	LTLtoSHE	OPtoCAB	OPtoCAB-TRP	ARtoCL	ARtoSHE-FA	CAtoCL	CAtoSHE	CAtoTA	CAtoTD	CA-CLtoSHE	CLtoSHE	CABtoTA	FAtoSHE	CPRtoTRP	CPRtoCAB	NWCtoTA	SHEtoTA	PRtoTRP	PRtoCAB	TRPtoCAB	TRP+OPtoCAB	SHE-TLtoTL	SHEtoTA	TRPtoTA-(SHE-CAB)	TLtoSHE-FA	TLtoCAB	TLtoTA	VSc	VtoCA	VtoSHE-FA	VtoCAB	VS	Vc	CABtoTA	TRPc	PrevDef
LTLtoSHE	,07	,01	,02	-,01	,03	,20	,08	,00	-,16	,06	,02	,00	,00	-,06	,00	,00	,00	,06	,01	,01	,01	-,20	-,01	,00	,14	,11	,01	-,27	,05	3,70	3,25	,00	-,26	-,01	-,02	-,01
OPtoCAB	,01	,03	,07	-,08	,09	-,65	,03	,00	-,48	-,01	,04	-,01	,01	,00	,00	-,01	-,01	,00	,01	,01	,04	-,54	-,01	-,01	,12	,07	,01	-,06	3,00	8,29	7,26	,00	1,47	-,02	,07	-,04
OPtoCAB-TRP	,02	,07	1,70	-,20	,27	-1,34	,24	,00	-,96	-,02	,26	-,01	,03	,02	,02	-,05	-,02	-,03	,04	,07	,15	-1,17	-,05	-,02	,36	,40	,05	-,26	3,98	23,52	18,33	,00	1,05	-,05	,66	-,08
ARtoCL	-,01	-,08	-,20	14,47	,32	13,78	-,25	,09	7,09	,18	-,43	,01	,00	-,07	-,02	,26	-,01	,06	-,03	-,05	-,13	10,31	,17	,02	-,11	-,37	-,06	1,96	-24,14	-49,20	-40,80	,00	-5,44	,13	-,47	,09
ARtoSHE-FA	,03	,09	,27	,32	39,60	-2,91	,64	,04	,59	,00	,64	-,04	,06	-,02	-,01	-,08	-,05	,03	,05	,05	,14	-1,91	-,13	-,07	65,77	,53	,09	-2,55	-8,78	18,06	17,95	,00	-3,11	-,15	-,03	-,17
CAtoCL	,20	-,65	-1,34	13,78	-2,91	573,86	-1,48	,39	242,02	1,20	-2,68	,34	-,49	,12	,05	1,47	,35	-,06	-,34	-,34	-,99	295,02	,98	,39	-1,76	-2,81	-,78	30,89	-136,24	-284,30	-247,71	-,01	-14,40	1,17	1,03	,49
CAtoSHE	,08	,03	,24	-,25	,64	-1,48	,81	,09	1,22	,11	,69	,00	-,02	-,07	-,01	-,05	,00	,07	,05	,06	,09	-1,86	-,14	-,01	,62	,64	,11	-,83	-11,94	10,74	11,14	,00	-,33	-,10	,13	-,13
CAtoTA	,00	,00	,00	,09	,04	,39	,09	,03	,30	,04	,05	,00	-,02	,00	,00	,02	,01	,00	,00	,00	,00	-,07	-,01	,00	,04	,04	,01	,10	-3,59	-1,59	-,74	,00	,68	,00	,05	-,01
CAtoTD	-,16	-,48	-,96	7,09	,59	242,02	1,22	,30	242,34	,48	,74	,15	-,34	,13	,02	,60	,16	-,13	-,13	-,13	-,61	247,61	,35	,17	-2,03	-2,71	-,82	20,31	-112,65	-213,96	-192,85	-,02	-11,90	,51	-,09	-,22
CA-CLtoSHE	,06	-,01	-,02	,18	,00	1,20	,11	,04	,48	,12	,00	,01	-,02	-,06	-,01	,05	,01	,05	,00	-,01	-,01	,22	,00	,01	,09	,05	,01	,04	-4,58	-3,79	-2,43	,00	,78	,01	,05	,00
CLtoSHE	,02	,04	,26	-,43	,64	-2,68	,69	,05	,74	,00	,70	-,01	,00	-,02	,00	-,09	-,01	,01	,05	,06	,10	-2,08	-,14	-,01	,53	,59	,10	-,88	-7,36	14,55	13,57	,00	-1,11	-,12	,08	-,14
CABtoTA	,00	-,01	-,01	,01	-,04	,34	,00	,00	,15	,01	-,01	,61	-,01	,00	,00	,01	1,56	-,01	,00	,00	-,01	,20	,00	,85	-,03	-,03	,00	-2,70	,90	-,69	-,46	,00	1,40	,01	,11	,00
FAtoSHE	,00	,01	,03	,00	,06	-,49	-,02	-,02	-,34	-,02	,00	-,01	,04	-,01	,00	-,02	-,02	,01	,01	,01	,02	-,18	,00	-,01	-,03	,05	,00	-,23	,48	5,62	3,03	,00	-,17	-,02	-,01	,00
CPRtoTRP	-,06	,00	,02	-,07	-,02	,12	-,07	,00	,13	-,06	-,02	,00	-,01	,16	,02	,00	,00	-,16	-,01	,01	,01	,22	,01	,00	-,13	-,11	-,01	-,08	,70	-3,11	-2,09	,00	-,27	,01	,13	,01
CPRtoCAB	,00	,00	,02	-,02	-,01	,05	-,01	,00	,02	-,01	,00	,00	,00	,02	,01	,00	,00	-,02	,00	,01	,01	,03	,00	,00	-,01	,00	,00	,03	,21	,18	,09	,00	-,07	,00	,07	,00
NWCtoTA	,00	-,01	-,05	,26	-,08	1,47	-,05	,02	,60	,05	-,09	,01	-,02	,00	,00	,05	,01	,00	-,01	-,01	-,03	,79	,03	,01	-,07	-,10	-,02	,29	-2,50	-6,86	-5,44	,00	,55	,03	,04	,03
SHEtoTA	,00	-,01	-,02	-,01	-,05	,35	,00	,01	,16	,01	-,01	1,56	-,02	,00	,00	,01	4,04	-,01	,00	,00	-,02	,24	,00	2,18	-,04	-,03	,00	-7,49	1,29	-,72	-,81	,00	1,93	,01	,12	-,01
PRtoTRP	,06	,00	-,03	,06	,03	-,06	,07	,00	-,13	,05	,01	-,01	,01	-,16	-,02	,00	-,01	,18	,01	-,01	-,01	-,17	-,01	,00	,13	,11	,01	,18	-,42	2,55	1,78	,00	,44	-,01	-,26	,00
PRtoCAB	,01	,01	,04	-,03	,05	-,34	,05	,00	-,13	,00	,05	,00	,01	-,01	,00	-,01	,00	,01	,01	,01	,02	-,27	-,01	,00	,03	,07	,01	-,19	-,26	3,29	2,35	,00	-,24	-,01	,00	-,02
TRPtoCAB	,01	,01	,07	-,05	,05	-,34	,06	,00	-,13	-,01	,06	,00	,01	,01	,01	-,01	,00	-,01	,01	,02	,03	-,28	-,02	-,01	,03	,08	,01	-,09	-,21	4,11	2,86	,00	-,22	-,02	,14	-,02
TRP+OPtoCAB	,01	,04	,15	-,13	,14	-,99	,09	,00	-,61	-,01	,10	-,01	,02	,01	,01	-,03	-,02	-,01	,02	,03	,07	-,83	-,03	-,01	,16	,16	,03	-,15	2,79	12,40	10,12	,00	1,24	-,03	,21	-,06
SHE-TLtoTL	-,20	-,54	-1,17	10,31	-1,91	295,02	-1,86	-,07	247,61	,22	-2,08	,20	-,18	,22	,03	,79	,24	-,17	-,27	-,28	-,83	302,78	,92	,24	-2,36	-3,27	-,95	24,89	-76,15	-224,03	-202,29	-,01	-10,00	,87	-,44	,47
SHEtoTA	-,01	-,01	-,05	,17	-,13	,98	-,14	-,01	,35	,00	-,14	,00	,00	,01	,00	,03	,00	-,01	-,01	-,02	-,03	,92	,04	,00	-,12	-,16	-,03	,30	,98	-5,89	-5,27	,00	-,01	,03	-,01	,04
CAB-TRPtoTA-(SHE-CAB)	,00	-,01	-,02	,02	-,07	,39	-,01	,00	,17	,01	-,01	,85	-,01	,00	,00	,01	2,18	,00	,00	-,01	-,01	,24	,00	1,20	-,05	-,03	,00	-3,71	,87	-,66	-,88	,00	1,67	,01	,02	-,01
TLtoSHE-FA	,14	,12	,36	-,11	65,77	-1,76	,62	,04	-2,03	,09	,53	-,03	-,03	-,13	-,01	-,07	-,04	,13	,03	,03	,16	-2,36	-,12	-,05	134,43	,84	,14	,19	2,86	-1,38	33,91	,00	2,07	-,11	,28	-,28
TLtoCAB	,11	,07	,40	-,37	,53	-2,81	,64	,04	-2,71	,05	,59	-,03	,05	-,11	,00	-,10	-,03	,11	,07	,08	,16	-3,27	-,16	-,03	,84	1,05	,18	-1,21	-4,75	36,41	29,59	,00	-,18	-,15	,10	-,17
TLtoTA	,01	,01	,05	-,06	,09	-,78	,11	,01	-,82	,01	,10	,00	,00	-,01	,00	-,02	,00	,01	,01	,01	,03	-,95	-,03	,00	,14	,18	,04	-,35	-,15	6,62	5,96	,00	,37	-,03	,02	-,03
VSc	-,27	-,06	-,26	1,96	-2,55	30,89	-,83	,10	20,31	,04	-,88	-2,70	-,23	-,08	,03	,29	-7,49	,18	-,19	-,09	-,15	24,89	,30	-3,71	,19	-1,21	-,35	5950,70	108,19	44,41	51,56	,16	4747,04	,40	10,17	1,49
VtoCA	,05	3,00	3,98	-24,14	-8,78	-136,24	-11,94	-3,59	-112,65	-4,58	-7,36	,90	,48	,70	,21	-2,50	1,29	-,42	-,26	-,21	2,79	-76,15	,98	,87	2,86	-4,75	-,15	108,19	13360,48	13760,86	13284,13	1,43	612,43	,47	-5,19	-6,08
VtoSHE-FA	3,70	8,29	23,52	-49,20	18,06	-284,30	10,74	-1,59	-213,96	-3,79	14,55	-,69	5,62	-3,11	,18	-6,86	-,72	2,55	3,29	4,11	12,40	-224,03	-5,89	-,66	-1,38	36,41	6,62	44,41	13760,86	27236,71	18912,93	1,46	1041,69	-7,22	-6,75	-17,03
VtoCAB	3,25	7,26	18,33	-40,80	17,95	-247,71	11,14	-,74	-192,85	-2,43	13,57	-,46	3,03	-2,09	,09	-5,44	-,81	1,78	2,35	2,86	10,12	-202,29	-5,27	-,88	33,91	29,59	5,96	51,56	13284,13	18912,93	17929,34	1,43	968,32	-5,78	-2,00	-16,30
VS	,00	,00	,00	,00	,00	-,01	,00	,00	-,02	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	-,01	,00	,00	,00	,00	,00	,16	1,43	1,46	1,43	,00	,32	,00	,00	,00
Vc	-,26	1,47	1,05	-5,44	-3,11	-14,40	-,33	,68	-11,90	,78	-1,11	1,40	-,17	-,27	-,07	,55	1,93	,44	-,24	-,22	1,24	-10,00	-,01	1,67	2,07	-,18	,37	4747,04	612,43	1041,69	968,32	,32	12407,05	,18	37,01	4,77
CABtoTA	-,01	-,02	-,05	,13	-,15	1,17	-,10	,00	,51	,01	-,12	,01	-,02	,01	,00	,03	,01	-,01	-,01	-,02	-,03	,87	,03	,01	-,11	-,15	-,03	,40	,47	-7,22	-5,78	,00	,18	,04	,00	,03
TRPc	-,02	,07	,66	-,47	-,03	1,03	,13	,05	-,09	,05	,08	,11	-,01	,13	,07	,04	,12	-,26	,00	,14	,21	-,44	-,01	,02	,28	,10	,02	10,17	-5,19	-6,75	-2,00	,00	37,01	,00	142,52	,17
PrevDef	-,01	-,04	-,08	,09	-,17	,49	-,13	-,01	-,22	,00	-,14	,00	,00	,01	,00	,03	-,01	,00	-,02	-,02	-,06	,47	,04	-,01	-,28	-,17	-,03	1,49	-6,08	-17,03	-16,30	,00	4,77	,03	,17	,92

Covariance (all)	LTLtoSHE	OPtoCAB	OPtoCAB-TRP	ARtoCL	ARtoSHE-FA	CAtoCL	CAtoSHE	CAtoTA	CAtoTD	CA-CLtoSHE	CLtoSHE	CABtoTA	FAtoSHE	CPRtoTRP	CPRtoCAB	NWCtoTA	SHEtoTA	PRtoTRP	PRtoCAB	TRPtoCAB	TRP+OPtoCAB	SHE-TLtoTL	SHEtoTA	TRPtoTA-(SHE-CAB)	TLtoSHE-FA	TLtoCAB	TLtoTA	VSc	VtoCA	VtoSHE-FA	VtoCAB	VS	Vc	CABtoTA	TRPc	PrevDef
LTLtoSHE	,06	,01	,03	-,01	,03	,19	,07	,00	-,16	,06	,02	,00	,00	-,06	,00	,00	,00	,06	,01	,01	,01	-,20	-,01	,00	,13	,11	,01	-,28	,04	3,58	3,15	,00	-,28	-,01	-,02	-,01
OPtoCAB	,01	,04	,10	-,08	,09	-,67	,03	,00	-,50	-,01	,04	-,01	,01	,00	,00	-,02	-,01	,00	,01	,01	,05	-,55	-,02	-,01	,13	,08	,01	-,15	3,10	8,92	7,73	,00	1,38	-,02	,06	-,04
OPtoCAB-TRP	,03	,10	3,25	-,23	,34	-1,56	,23	-,01	-1,15	-,04	,27	-,02	,05	,03	,04	-,06	-,02	-,04	,05	,10	,20	-1,36	-,06	-,03	,49	,47	,06	-,80	3,90	28,46	20,78	,00	,20	-,07	,58	-,09
ARtoCL	-,01	-,08	-,23	13,90	,29	13,24	-,25	,08	6,77	,18	-,43	,01	,00	-,07	-,02	,25	-,01	,06	-,03	-,06	-,14	9,90	,17	,02	-,13	-,38	-,06	1,99	-23,07	-48,01	-40,01	,00	-5,34	,13	-,43	,11
ARtoSHE-FA	,03	,09	,34	,29	37,89	-2,96	,67	,05	,62	,00	,67	-,04	,06	-,02	-,01	-,09	-,05	,03	,06	,06	,15	-1,96	-,13	-,06	62,87	,57	,09	-2,62	-7,77	22,14	21,30	,00	-3,34	-,15	-,05	-,18
CAtoCL	,19	-,67	-1,56	13,24	-2,96	550,99	-1,53	,38	232,95	1,19	-2,72	,32	-,49	,12	,05	1,46	,32	-,06	-,34	-,35	-1,02	284,30	,98	,36	-1,90	-2,87	-,78	32,08	-136,88	-288,35	-251,60	-,01	-13,36	1,16	1,09	,49
CAtoSHE	,07	,03	,23	-,25	,67	-1,53	,84	,09	1,26	,11	,73	,00	-,02	-,07	-,01	-,05	,00	,06	,05	,06	,09	-1,86	-,15	-,01	,66	,67	,11	-,91	-11,63	12,69	13,19	,00	-,48	-,10	,10	-,14
CAtoTA	,00	,00	-,01	,08	,05	,38	,09	,03	,31	,04	,05	,00	-,02	,00	,00	,02	,01	,00	,00	,00	,00	-,07	-,01	,00	,04	,04	,01	,11	-3,64	-1,55	-,70	,00	,72	,00	,05	-,01
CAtoTD	-,16	-,50	-1,15	6,77	,62	232,95	1,26	,31	239,34	,49	,76	,13	-,34	,12	,01	,59	,14	-,12	-,13	-,14	-,64	240,05	,34	,16	-2,15	-2,79	-,83	19,56	-110,69	-217,52	-195,74	-,02	-8,52	,50	-,11	-,25
CA-CLtoSHE	,06	-,01	-,04	,18	,00	1,19	,11	,04	,49	,11	-,01	,01	-,02	-,05	-,01	,05	,01	,05	,00	-,01	-,02	,24	,00	,01	,08	,04	,01	,10	-4,71	-4,09	-2,70	,00	,87	,02	,05	,01
CLtoSHE	,02	,04	,27	-,43	,67	-2,72	,73	,05	,76	-,01	,74	-,01	,00	-,02	,00	-,10	-,01	,01	,05	,07	,11	-2,10	-,15	-,01	,58	,63	,10	-1,01	-6,93	16,80	15,89	,00	-1,35	-,12	,05	-,15
CABtoTA	,00	-,01	-,02	,01	-,04	,32	,00	,00	,13	,01	-,01	,59	-,01	,00	,00	,01	1,49	,00	,00	,00	-,01	,18	,00	,81	-,03	-,03	,00	-2,55	,87	-,73	-,50	,00	1,38	,01	,11	,00
FAtoSHE	,00	,01	,05	,00	,06	-,49	-,02	-,02	-,34	-,02	,00	-,01	,04	-,01	,00	-,02	-,02	,01	,01	,01	,02	-,19	,00	-,01	-,03	,05	,00	-,25	,57	5,84	3,19	,00	-,25	-,02	-,01	-,01
CPRtoTRP	-,06	,00	,03	-,07	-,02	,12	-,07	,00	,12	-,05	-,02	,00	-,01	,15	,02	,00	,00	-,15	-,01	,01	,01	,21	,01	,00	-,12	-,11	-,01	-,11	,73	-2,95	-2,01	,00	-,20	,01	,12	,01
CPRtoCAB	,00	,00	,04	-,02	-,01	,05	-,01	,00	,01	-,01	,00	,00	,00	,02	,01	,00	,00	-,02	,00	,01	,01	,02	,00	,00	-,01	,00	,00	,02	,23	,25	,13	,00	-,07	,00	,06	,00
NWCtoTA	,00	-,02	-,06	,25	-,09	1,46	-,05	,02	,59	,05	-,10	,01	-,02	,00	,00	,05	,01	,00	-,01	-,01	-,03	,79	,03	,01	-,07	-,11	-,02	,33	-2,61	-7,17	-5,75	,00	,62	,03	,04	,03
SHEtoTA	,00	-,01	-,02	-,01	-,05	,32	,00	,01	,14	,01	-,01	1,49	-,02	,00	,00	,01	3,86	-,01	,00	,00	-,02	,21	,00	2,09	-,03	-,03	,00	-7,13	1,25	-,63	-,76	,00	1,89	,01	,11	-,01
PRtoTRP	,06	,00	-,04	,06	,03	-,06	,06	,00	-,12	,05	,01	,00	,01	-,15	-,02	,00	-,01	,17	,01	-,01	-,01	-,18	-,01	,00	,12	,10	,01	,22	-,37	2,55	1,82	,00	,40	-,01	-,24	,00
PRtoCAB	,01	,01	,05	-,03	,06	-,34	,05	,00	-,13	,00	,05	,00	,01	-,01	,00	-,01	,00	,01	,01	,01	,02	-,27	-,01	,00	,04	,08	,01	-,20	-,20	3,53	2,59	,00	-,25	-,01	,00	-,02
TRPtoCAB	,01	,01	,10	-,06	,06	-,35	,06	,00	-,14	-,01	,07	,00	,01	,01	,01	-,01	,00	-,01	,01	,02	,03	-,30	-,02	-,01	,04	,09	,01	-,13	-,18	4,41	3,14	,00	-,26	-,02	,13	-,02
TRP+OPtoCAB	,01	,05	,20	-,14	,15	-1,02	,09	,00	-,64	-,02	,11	-,01	,02	,01	,01	-,03	-,02	-,01	,02	,03	,08	-,85	-,03	-,02	,18	,17	,03	-,27	2,92	13,32	10,87	,00	1,12	-,03	,19	-,07
SHE-TLtoTL	-,20	-,55	-1,36	9,90	-1,96	284,30	-1,86	-,07	240,05	,24	-2,10	,18	-,19	,21	,02	,79	,21	-,18	-,27	-,30	-,85	292,55	,92	,22	-2,48	-3,33	-,95	24,35	-77,32	-229,17	-207,02	-,01	-7,61	,87	-,40	,45
SHEtoTA	-,01	-,02	-,06	,17	-,13	,98	-,15	-,01	,34	,00	-,15	,00	,00	,01	,00	,03	,00	-,01	-,01	-,02	-,03	,92	,04	,00	-,13	-,16	-,03	,33	,92	-6,19	-5,59	,00	,02	,03	,00	,04
CAB-TRPtoTA-(SHE-CAB)	,00	-,01	-,03	,02	-,06	,36	-,01	,00	,16	,01	-,01	,81	-,01	,00	,00	,01	2,09	,00	,00	-,01	-,02	,22	,00	1,15	-,06	-,03	,00	-3,52	,90	-,65	-,87	,00	1,69	,01	,02	-,01
TLtoSHE-FA	,13	,13	,49	-,13	62,87	-1,90	,66	,04	-2,15	,08	,58	-,03	-,03	-,12	-,01	-,07	-,03	,12	,04	,04	,18	-2,48	-,13	-,06	128,49	,91	,15	-,09	2,88	4,40	37,47	,00	1,21	-,12	,24	-,30
TLtoCAB	,11	,08	,47	-,38	,57	-2,87	,67	,04	-2,79	,04	,63	-,03	,05	-,11	,00	-,11	-,03	,10	,08	,09	,17	-3,33	-,16	-,03	,91	1,11	,18	-1,37	-4,56	39,42	32,72	,00	-,88	-,15	,07	-,18
TLtoTA	,01	,01	,06	-,06	,09	-,78	,11	,01	-,83	,01	,10	,00	,00	-,01	,00	-,02	,00	,01	,01	,01	,03	-,95	-,03	,00	,15	,18	,04	-,38	-,11	6,96	6,31	,00	,18	-,03	,02	-,03
VSc	-,28	-,15	-,80	1,99	-2,62	32,08	-,91	,11	19,56	,10	-1,01	-2,55	-,25	-,11	,02	,33	-7,13	,22	-,20	-,13	-,27	24,35	,33	-3,52	-,09	-1,37	-,38	5696,79	98,67	24,82	33,92	,15	4541,06	,44	9,84	1,60
VtoCA	,04	3,10	3,90	-23,07	-7,77	-136,88	-11,63	-3,64	-110,69	-4,71	-6,93	,87	,57	,73	,23	-2,61	1,25	-,37	-,20	-,18	2,92	-77,32	,92	,90	2,88	-4,56	-,11	98,67	13347,23	13746,87	13248,47	1,37	565,46	,37	-5,40	-6,06
VtoSHE-FA	3,58	8,92	28,46	-48,01	22,14	-288,35	12,69	-1,55	-217,52	-4,09	16,80	-,73	5,84	-2,95	,25	-7,17	-,63	2,55	3,53	4,41	13,32	-229,17	-6,19	-,65	4,40	39,42	6,96	24,82	13746,87	27177,61	19027,31	1,41	953,87	-7,54	-6,95	-18,01
VtoCAB	3,15	7,73	20,78	-40,01	21,30	-251,60	13,19	-,70	-195,74	-2,70	15,89	-,50	3,19	-2,01	,13	-5,75	-,76	1,82	2,59	3,14	10,87	-207,02	-5,59	-,87	37,47	32,72	6,31	33,92	13248,47	19027,31	18020,70	1,38	891,72	-6,10	-3,27	-17,06
VS	,00	,00	,00	,00	,00	-,01	,00	,00	-,02	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	,00	-,01	,00	,00	,00	,00	,00	,15	1,37	1,41	1,38	,00	,30	,00	,00	,00
Vc	-,28	1,38	,20	-5,34	-3,34	-13,36	-,48	,72	-8,52	,87	-1,35	1,38	-,25	-,20	-,07	,62	1,89	,40	-,25	-,26	1,12	-7,61	,02	1,69	1,21	-,88	,18	4541,06	565,46	953,87	891,72	,30	12543,75	,24	35,00	4,42
CABtoTA	-,01	-,02	-,07	,13	-,15	1,16	-,10	,00	,50	,02	-,12	,01	-,02	,01	,00	,03	,01	-,01	-,01	-,02	-,03	,87	,03	,01	-,12	-,15	-,03	,44	,37	-7,54	-6,10	,00	,24	,04	,01	,03
TRPc	-,02	,06	,58	-,43	-,05	1,09	,10	,05	-,11	,05	,05	,11	-,01	,12	,06	,04	,11	-,24	,00	,13	,19	-,40	,00	,02	,24	,07	,02	9,84	-5,40	-6,95	-3,27	,00	35,00	,01	136,21	,18
PrevDef	-,01	-,04	-,09	,11	-,18	,49	-,14	-,01	-,25	,01	-,15	,00	-,01	,01	,00	,03	-,01	,00	-,02	-,02	-,07	,45	,04	-,01	-,30	-,18	-,03	1,60	-6,06	-18,01	-17,06	,00	4,42	,03	,18	,94

APPENDIX E: FINAL DISCRIMINANT MODEL RESULTS

Correct Predictions for different cut off points

	Original		Holdout	
Prior	Cor. Def.	Cor. Non-Def.	Cor. Def	Cor. Non-Def.
17.5%	96.9%	32.1%	87.5%	37.8%
20.0%	96.9%	38.1%	75.0%	41.4%
22.5%	94.5%	42.5%	75.0%	45.0%
25.0%	91.4%	46.2%	75.0%	48.6%
27.5%	91.4%	50.0%	75.0%	53.0%
30.0%	89.1%	53.6%	75.0%	57.0%
32.5%	87.5%	56.9%	75.0%	62.7%
35.0%	82.0%	60.6%	75.0%	67.5%
37.5%	78.9%	63.1%	75.0%	72.3%
40.0%	74.2%	65.7%	75.0%	73.1%
42.5%	74.2%	68.7%	75.0%	75.9%
45.0%	73.4%	70.8%	62.5%	78.7%
47.5%	72.7%	72.9%	62.5%	80.3%
50.0%	70.3%	75.2%	62.5%	83.1%
52.5%	67.2%	77.5%	50.0%	83.9%
55.0%	64.8%	79.7%	37.5%	84.7%
57.5%	61.7%	82.0%	37.5%	84.7%
60.0%	58.6%	83.8%	37.5%	88.0%
62.5%	57.0%	85.2%	37.5%	90.4%
65.0%	50.8%	87.1%	37.5%	91.2%
67.5%	48.4%	88.7%	37.5%	92.0%
70.0%	42.2%	90.1%	37.5%	92.8%
72.5%	40.6%	91.2%	37.5%	92.8%
75.0%	35.2%	92.2%	37.5%	94.8%
77.5%	31.3%	93.3%	37.5%	95.2%
80.0%	27.3%	94.5%	37.5%	96.4%
82.5%	22.7%	95.5%	37.5%	97.6%

APPENDIX F: SIGNIFICANT VARIABLES IN DIFFERENT PERIODS

1/1999 - 6/2001

Variables Entered/Removed									
		Wilks' Lambda							
						Exact F			
Step	Entered	Statistic	df1	df2	df3	Statistic	df1	df2	Sig.
1	CPRtoCAB	0,954	1	1	703	33,806	1	703	0
2	PrevDef	0,915	2	1	703	32,732	2	702	0
3	FAtoSHE	0,897	3	1	703	26,955	3	701	0
4	DCABtoTA	0,889	4	1	703	21,892	4	700	0

6/2001 - 12/2003

Variables Entered/Removed									
		Wilks' Lambda							
						Exact F			
Step	Entered	Statistic	df1	df2	df3	Statistic	df1	df2	Sig.
1	OPtoCAB	0,881	1	1	723	97,357	1	723	0
2	OPtoCAB-TRP	0,86	2	1	723	58,553	2	722	0
3	CA-CLtoSHE	0,853	3	1	723	41,322	3	721	0

12/2003 - 6/2006

Variables Entered/Removed									
		Wilks' Lambda							
						Exact F			
Step	Entered	Statistic	df1	df2	df3	Statistic	df1	df2	Sig.
1	OPtoCAB	0,976	1	1	772	19,045	1	772	0
2	TRPtoCAB	0,968	2	1	772	12,852	2	771	0
3	CPRtoCAB	0,963	3	1	772	9,889	3	770	0

6/2006 - 5/2009

Variables Entered/Removed									
		Wilks' Lambda							
						Exact F			
Step	Entered	Statistic	df1	df2	df3	Statistic	df1	df2	Sig.
1	DCABtoTA	0,952	1	1	806	40,538	1	806	0
2	OPtoCAB	0,924	2	1	806	33,146	2	805	0
3	PrevDef	0,912	3	1	806	25,88	3	804	0
4	TRPc	0,903	4	1	806	21,596	4	803	0
5	CAtoTD	0,896	5	1	806	18,61	5	802	0

APPENDIX G: FACTOR ANALYSIS RESULTS

Rotated Component Matrix (Principle Components with Varimax Rotation)

	Component										
	1	2	3	4	5	6	7	8	9	10	11
LTLtoSHE	,162	**,779**	-,004	,181	,050	-,003	,283	,009	-,038	-,007	-,097
OPtoCAB	,249	,042	-,033	-,190	,137	-,137	,327	,044	,079	**,720**	,000
OPtoCAB-TRP	,138	,003	,000	-,061	,029	-,009	**,584**	,016	,003	,066	-,033
ARtoCL	-,147	,050	,003	,151	-,058	,126	,093	,018	,014	-,046	**,799**
ARtoSHE-FA	,090	-,003	-,004	-,016	,000	,003	,009	**,971**	-,004	,018	,022
CAtoCL	-,134	,039	,006	,119	-,023	**,814**	,049	-,006	,004	-,002	,063
CAtoSHE	**,879**	,125	,001	,329	-,024	,059	,006	,043	-,006	,016	-,055
CAtoTA	,336	-,043	,010	**,859**	-,072	,035	-,050	,011	,035	,052	,137
CAtoTD	-,001	-,038	,002	,062	-,047	**,946**	-,074	,004	,003	-,019	-,012
CA-CLtoSHE	,003	**,545**	,007	**,776**	-,049	,059	,109	,004	,002	-,039	,038
CLtoSHE	**,937**	-,081	-,002	,046	-,006	,040	-,036	,044	-,007	,032	-,073
DCABtoTA	-,019	-,008	**,997**	,033	,004	,007	-,006	-,002	-,006	-,010	-,008
FAtoSHE	,089	,158	-,050	**-,713**	,040	-,054	,289	,008	,006	,110	,241
CPRtoTRP	-,117	**-,912**	,001	,031	-,014	,003	,180	-,004	-,009	,007	-,027
CPRtoCAB	-,029	**-,559**	-,009	,055	,015	,027	**,653**	-,022	-,025	-,087	-,141
NWCtoTA	**-,551**	,075	,010	**,740**	-,083	,127	,009	-,012	,019	-,064	,193
DSHEtoTA	-,003	,000	**,997**	,003	,000	,001	,003	,000	-,011	-,004	,000
PRtoTRP	,099	**,884**	-,005	-,053	,018	-,002	-,210	,005	,014	-,026	,026
PRtoCAB	**,754**	,288	-,015	-,235	,053	-,032	,300	,011	-,026	,060	,033
TRPtoCAB	**,572**	-,163	-,014	-,124	,041	-,002	**,692**	-,001	-,026	-,013	-,073
TRP+OPtoCAB	,482	-,059	-,031	-,200	,118	-,097	**,602**	,030	,041	,497	-,040
SHE-TLtoTL	-,157	-,008	,005	-,018	-,027	**,943**	-,011	-,003	,006	-,015	,043
SHEtoTA	**-,942**	-,030	,006	,008	-,036	,117	-,018	-,025	,001	-,139	,105
CAB-TRPtoTA-(SHE-CAB)	-,016	,002	**,997**	,019	,002	,005	-,020	-,003	-,006	,001	,002
TLtoSHE-FA	,029	,023	-,001	,014	,008	-,009	,014	**,974**	,000	,015	-,020
TLtoCAB	**,818**	,260	-,009	-,020	,069	-,092	,260	,024	-,005	,110	,049
TLtoTA	**,761**	,056	,000	,121	,083	-,216	,119	,012	,006	,146	,090
VSc	-,010	-,006	-,044	,001	,007	,022	-,009	-,002	**,868**	-,043	-,012
VtoCA	-,094	-,035	,006	-,059	**,924**	-,023	-,032	-,003	-,013	,059	-,038
VtoSHE-FA	,144	,030	-,001	-,071	**,860**	-,033	,072	-,007	-,009	,172	,035
VtoCAB	,154	,016	-,003	-,029	**,926**	-,042	,040	,008	-,004	,177	,011
VS	-,011	,056	,005	-,007	**,632**	-,013	,041	,013	,122	-,307	-,032
Vc	-,009	,003	,024	,026	,060	-,011	,005	-,001	**,875**	,017	-,024
CABtoTA	**-,780**	-,095	,035	,437	-,037	,131	-,127	-,036	,000	-,143	-,053
TRPc	-,052	,028	,005	,069	-,025	,021	,184	,011	,038	,019	-,475
PrevDef	-,148	,024	-,012	-,039	-,038	-,052	,064	-,003	,059	**-,685**	,057

REFERENCES

Altman, E.I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, Journal of Finance, Vol. 23, September, pp. 589-609.

Altman, E.I. (1973). Predicting railroad bankruptcies in America, Bell Journal of Economics and Management Science, Spring.

Altman, E.I., Margaine M., Schlosser M. and Vernimmen P. (1974) Financial and Statistical Analysis for Commercial Loan Evaluation: A French Experience. The Journal of Financial and Quantitative Analysis, Vol. 9, No. 2, March, pp 195-211.

Altman, E.I. and Lorris, B. (1976). A financial early warning system for over the counter brokers and dealers, Journal of Finance, Vol. 31, September, pp. 1201-1217.

Altman E.I. and Eisenbeis A.R. (1978). Financial Applications of Discriminant Analysis: A Clarification, Journal of Financial and Quantitative Analysis, Vol.13, No.1, March, pp. 185-195.

Altman E.I. (2005). An Emerging Market Credit Scoring System for Corporate Bonds. Emerging Markets Review, Vol. 6, pp. 311-323.

Aminian F., Suarez E.D., Aminian M. and Walz D.T. (2006). Forecasting Economic Data with Neural Networks, Computational Economics, Vol. 28, pp. 71-88.

Back, B., Laitinen, S.T. and Wezel, M. (1996). Choosing Bankruptcy Predictors using Discriminant Analysis, Logit Analysis and Genetic Algorithms, Technical Report, No. 40, Turcu Center for Computer Science (TUCS).

Beaver, W. (1966). Financial ratios as predictors of failure. Empirical research in accounting: selected studies. Journal of Accounting Research, (Supplement) Vol. 4, pp. 71-111.

Beaver, W. (1968a). Alternative financial ratios as predictors of failure. The Accounting Review, Vol. XLIII, January, pp. 113-122.

Beaver, W. (1968b), Market prices, financial ratios and prediction of failure, Journal of Accounting Research, Autumn, pp. 179-192.

Blum, M. (1974). Failing company discriminant analysis. Journal of Accounting Research, Spring, pp. 1-21.

Brockett P.L., Golden L.L., Jang J. and Yang C. (2006). A Comparison of Neural Network, Statistical Methods, And Variable Choice for Life Insurer's Financial Distress Prediction. The Journal of Risk and Insurance, Vol.73, No.3, pp.397-419.

Churchill Jr., G.A. and Iacobucci D. (2005). Marketing Research - Methodological Foundations, Ninth Edition, Thomson-South Western

Cooley W.W. and Lohnes P.R. (1971). Multivariate Data Analysis, Fourth Edition, John Wiley and Sons Inc

Deakin, E. (1972). A discriminant analysis of predictors of business failure, Journal of Accounting Research, Spring, pp. 167-179.

Dimson E. and Marsh P. (1995). Capital Requirements for Securities Firms. The Journal of Finance, Vol.50 No.3, Papers and Proceedings Fifty-Fifth Annual Meeting, American Finance, Association, Washington D.C., January 6-8, 1995, July, pp.821-851.

Eiteman, W.J. (1933). Regulation of Broker's Loans. The American Economic Review, Vol 23, No.3, September, pp. 456-465.

Edmister, R.O. (1972). An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction. Journal of Financial and Quantitative Analysis, March, pp. 1477-1493.

Haykin, S. (1994). Neural Networks: A Comprehensive Foundation. Saddle River, NJ: Prentice Hall

Joy, O.M. and Tollefson, J.O. (1995). On the financial applications of discriminant analysis. Journal of Financial and Quantitative Analysis, Vol. 10 No. 5, December, pp. 723-739.

Lachenbruch, P.A. (1967). An almost unbiased method of obtaining confidence intervals for the probability of misclassification in discriminant analysis. Biometrics, Vol 23, pp. 639-645.

Lattin J., Carroll J.D., and Green P.E. (2003). Analyzing Multivariate Data, Duxbury Applied Series, Thomson – Brooks / Cole Publications

Libby, R. (1975). Accounting ratios and the prediction of failure: some behavioral evidence. Journal of Accounting Research, Spring, pp. 150-161.

McNelis P.D. (2005) Neural Networks in Finance: Gaining Predictive Edge in the Market, Elsevier Academic Press

Meyer P.A. and Pifer H.W. (1970). Prediction of Bank Failures, The Journal of Finance, Vol. 25, No. 4, September, pp. 853-868

Moyer, R. (1977) ''Forecasting financial failure: a reexamination'', Financial Management, Spring.

Ohlson, J.A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. Journal of Accounting Research, Vol. 18, Spring, pp. 109-131.

Reynolds S., Fowles R., Gander J., Kunaporntham W., and Ratanakomut S. (2002) Forecasting Probability of Failure of Thailand's Financial Companies in the Asian Financial Crisis. Economic Development and Cultural Change, Vol.1, pp.237-246.

Sinkey Jr., J.F. (1975). A Multivariate Statistical Analysis of the Characteristics of Problem Banks. The Journal of Finance, Vol. 30, No. 1, March, pp. 21-36.

Sharma, S. (1996). Applied Multivariate Techniques. Wiley Publications

Sharma, S. and Mahajan, V. (1980). Early warning indicators of business failure. Journal of Marketing, Fall, pp. 80-89.

Shumway T. (2001). Forecasting Bankruptcy More Accurately, A Simple Hazard Model. The Journal of Business, Vol.74, No.1, January, pp.101-124.

Siegel J. and Shim J. (2003). The Artifical Intelligence Handbook: Business Applications in Accounting, Banking, Finance, Management and Marketing. Thomson-South Western

Tam K.R., and Kiang M.Y. (1992). Managerial Applications of Neural Networks: The Case of Bank Failure Predictions, Management Science, Vol. 38, No.7, July, pp.926-947.

Turner A. (2009). The Turner Review: A regulatory response to the global banking crisis, FSA Publications

Uğurlu M. and Aksoy H. (2006) Prediction of Corporate Financial Distress in an Emerging Market: the Case of Turkey. Cross Cultural Management: An International Journal, Vol.13, No.4, pp. 277-295.

Yıldıran T. (1998). Mali Oranlar ve Diskriminant Modeli İle Aracı Kurumların Mali Açıdan Başarılı-Başarısız Olarak Sınıflandırılması – Çok Boyutlu Bir Model Denemesi, Sermaye Piyasası Kurulu Yeterlik Etüdü, Dönem 12-4.

Zmijewski M.E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. Journal of Accounting Research, Vol. 22, pp 59-82.