AN EARLY WARNING MODEL FOR TURKISH INSURANCE COMPANIES

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ABSTRACT

AN EARLY WARNING MODEL FOR TURKISH INSURANCE COMPANIES

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In Turkey, insurance companies have some obligations to be solvent and for this reason they are regularly audited according to defined constraints. There are some models and methods in order to analyze company performances. One of them is an early warning model that is constructed by using some financial ratios. The aim of the study is to determine how Solvency requirements affected the financial stability of Turkish insurance companies last years. Firstly, the proposed model takes into account the financial ratios related to liquidity, profitability, and other factors regarding to the country specific properties which was also used in study done by Genc (2006). Historical data on companies' financial indicators are evaluated based on comparative linear model estimation methods to determine the company's financial position which functions as an early warning indicator. In this study, used four methods have been employed to construct the predictor model as an early warning system which are linear regression, Multiperod Discriminant analysis, Logistic and Bayesian Regression. Financial details of 41 insurance companies which acted in the period of 1998-2012 in Turkish market was used. After determination of best fitted model, 2013 prediction was applied to all existence insurance companies.

Keywords: Linear Regression, Multivariate Discriminant Analysis, Logistic Regression, Bayesian Regression, Ratio Analysis

ÖZ

TÜRKİYE' DEKİ SİGORTA ŞİRKETLERİ İÇİN BİR ERKEN UYARI MODELİ

Ocak, Gizem
Yüksek Lisans, Finansal Matematik
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Türkiye'de sigorta şirketleri yükümlülüklerini karşılamak amacıyla bazı sorumluluklara sahiptirler ve bu sebeple, belirlenmiş bazı kriterlere göre düzenli olarak denetim sürecinden geçerler. Şirket performansını ölçmek için kullanılan bazı methodlar ve modeller vardır. Bunlardan bir tanesi Erken Uyarı Modeli olup, bu model şirketlerin bazı finansal oranlarından yararlanılarak oluşturulur. Bu çalışmanın amacı, son yıllarda Türkiye'de ki sigorta şirketlerinin yükümlülüklerinin karşılanması ile ilgili yapılan gerekliliklerin sektördeki finansal durumu açısından etkisini ölçmektir. İlk aşamada, Ahmet Genç tarafından daha önce 2006 yılında yapılan çalışmada kullanılan likidite, karlılık ve ülkenin finasal yapısına özgü diğer finansal oranların dikkate alınması ile önerilen model oluşturulmuştur. Sigorta şirketlerinin geçmiş finansal verileri kullanılarak, lineer tahmin edici modeller ile erken uyarı göstergesi olan model oluşturulmuştur. Tahmin edici modeli kurmak için 4 ayrı lineer model kullanılmış olup bunlar: Lineer Regresyon, Çok Değişkenli Ayırma Analizi, Logistik ve Bayesyen Regresyondur. Analizde, 1998-2012 döneminde Türkiye'de faaliyet gösteren 41 sigorta şirketinin finansal tabloları kullanılmış ve en uygun model belirlendikten sonra, 2013 yılı için tahmin yapılmıştır.

Anahtar Kelimeler: Lineer Regresyon, Çok Değişkenli Ayırma Analizi, Logistik Regresyon, Bayesyen Regresyon, Rasyo Analizi

To My Family

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LIST OF ABBREVIATIONS

EU	European Union
Z	Z-score
$\phi(.)$	Cumulative Normal Distribution Function
MDA	Multiple Discriminant Analysis
L	Maximum Likelihood Function
KPI	Key Performance Indicator
SCR	Solvency Capital Requirement
MCR	Minimum Capital Requirement
VaR	Value-at-Risk
X_1	Liquid Asset/Total Asset
X_2	Premium Collection Ratio
X_3	Net Premium Receivables(Insurance and Agency Op.s)/Total Asset
X_4	Loss/Premium
X_5	Profit/Paid Capital
X_6	Premium Production /Coverage
X_7	Payables on Reinsurance Op./Equity
X_8	Liability(Short Term)/Liquid Asset
X_9	Total Reserve/Net Premium
X_{10}	Total Reserve/Liquid Asset
X_{11}	Technical Profit/Premium
X_{12}	Total Income/Total Asset
X_{13}	Total Payables(Long and Short Term)/Equity
X_{14}	Reinsurance share/Gross Premium
A	Age
Y	Dependent variable
$\hat{Y}$	Predicted Dependent Variable
$\hat{Y}_D$	Predicted model including duration of dependent variable
LA	Liquid Asset
TA	Total Asset
Loss Ratio	Loss/Profit

TP	Technical Profit
PoRO	Payables on Reinsurance Operations
STL	Short Term Liability
TP(LS)	Total Payables (Long and Short Term)
RS	Reinsurance Share
GP	Gross Premium
TI	Total Income
Y	Dependent Variable
R^2	Coefficient of Determination
Y_D	Dependent variable in the analysis of additional variables
σ^2	Variance
P	Probability of being the group of failed firms
I	Indicator for Insolvent Companies
W	Indicator for Warning Companies
S	Indicator for Solvent Companies

CHAPTER 1

INTRODUCTION

Generally, all corporations have an obligation to maintain their business in order to not being insolvent. Indeed, insurance companies have the similar responsibilities both to their policy holders and state which are framed by national and in the last decade, also by the international regulations. In policyholders' aspect, the insurance company should have adequate amount of reserve to meet the demand resulting from the claims, and attaining the certain level of financial stability for its existence in the insurance sector. In the time period of existing of the companies, they may collect significant amount of premium regardless of any risk. However, this could be resulted in even insolvency or bankruptcy while being faced with unexpected loss amounts which may be over the equity of firm. Therefore, stability or tendency of the company should be under control accurately [37].

Until today, since a lot of companies have become failed regarding various reasons, prediction of bankruptcy has been center of the interest in all economies including banks and insurance businesses.Therefore, the risk of failure is a great concern of all enterprises and it has been examined by lots of analyses and models to determine it. For instance, companies who are risk averse regard precisely actuarial calculations such as reserve, pricing and loss predictions, etc. Therefore, the methods of those calculations are significant both for profitability and credibility of firms. With accurate and correct estimations, a corporate obtains profitable and sustainable outcomes [13].

As it is mentioned above, there are various methods and ways to define the risk level such as Solvency I and II. These regimes are the important steps which uses both stochastic and deterministic approaches. Solvency II regime gives some constraints to fulfil financial responsibilities in a common way. With that study, the aim is to create a unique and common insurance market for EU and strengthen protection of insured people. The quantification of this liability is the main concern of Solvency II regulations [31]. In addition, Solvency Margin which is older then Solvency regimes and still applicable in some economies including Turkey is an another approach which is a regulated minimum excess on assets of insurer over its liabilities and it can be considered as capital adequacy requirements similarly like applied for banks. Since solvency margin is on the basis of ratio (static), Solvency regimes are more complicated and advanced if compared [18]. However, selection of the method depends on the applicable data and conditions of the economy because transparency and eligibility of the used data differs from the conditions of the sector to another also, between countries [22].

In insurance business, financial and technical statements which are balance sheets, income statements and some technical reports have been employed to investigate condition of the insurer. After examinations, having profitability in both total and technical results demonstrates as a good sign for the company. However, profitability is not the only indicator, but also liquidity, financial performance and trend in a given period are remarkably significant pointers [44]. There are many methods concerning measuring the liability of an insurance company to be solvent. One of them is to use financial ratios in order to demonstrate weak and strong side of company. This method can be used for comparing market average ratios by the ratios set by the state and laws. Horizontal, vertical, trend and ratio analyses are some of them and are utilized to understand the financial condition of the firm [10]. Financial ratios also can be employed in some models as random variables to give signals of company's future as an early warning system. In addition, early preventions and precautions are also required in order the company to be solvent [15]. It is important to emphasize that ratios vary with respect to the type of insurance policy and the benefit promised. Hence, the choice of financial ratio as determinant is considerable to make judgements on the insolvency pattern. Besides, they are good indicators of the corporates on their own, they are employed in different linear and non-linear models.

1.1 Literature Survey

In finance, financial ratios firstly have been taken into account as a representative of a corporation's condition (Beaver (1966)). Beaver (1966) proposed 6 groups of financial ratios employed to test the predictive ability of ratios by applying Dichotomous Classification Test. Data has been collected from Moody's Industrial Manual during the period 1954-1964. The test was constructed with two sample of firms including 79 non-failed and 79 failed firms. Failed firms were categorized with regard to asset sizes and industry types. Then, 79 non-failed firms were selected for each failed firm. Since the random selection of the firms would be inappropriate to capture the difference between successful and distress companies, they have been chosen according to the specific features such as asset sizes and industry types. Furthermore, selection of the corporation randomly could have been set to the defined value but, because of determining the amount would be difficult, matching process have been applied. Firstly, mean values of each ratios for both failed and non-failed firms have been compared and this process have been called a profile analysis. Then, dichotomous classification test was used and 14 financial ratios chosen due to the ability of detecting insolvency of a firm were calculated for each firm. The set of firms were separated into two sub sample and in each sub sample, firms were ranked. This classification process was made regarding to the selection of the smallest ratio and that ratio was taken as a critical value for the other subgroup and as a result of the study, it is obtained that ratios are the significant predictors while determining probability of failure. Also, classification of the firms has an significant effect on distinguishing the corporations. In his study, he classified the firms with 78% exactitude five year before bankruptcy [14].

Multiple Discriminant Analysis (MDA) generally examined in biological and behavioural sciences in earlier years has been tried (Altman (1968)) by employing 22 financial ratios to 66 manufacturing firms which composed of 33 failed and 33 non-failed ones getting into a model. Bankrupted group is not completely homogeneous compared to Beaver (1966) due to the asset sizes, firms were chosen for defined asset size interval (1946-1966). And the non-failed firms were chosen in the same way of asset size interval existing in 1966. For instance, if a firm could be seen insolvent because of poor profitability, however its high liquidity could sign to be regarded as acceptable. Therefore, MDA was purposed to eliminate it since the traditional ratio analysis may not capture the interaction between the indicators. It has been used to examine the prediction of failure by utilizing financial and economical ratios and the method has been applied to derive a linear combination of those selected ratios which brings out the best result similarly regression analysis. With this way, interaction between ratios have been eliminated and effects of multiple indicators have been seen in result index. Ratios have been selected related to liquidity, profitability, leverage, solvency and activity measurements. As a result of the research, the model below with 95% accuracy has been obtained as a best choice while predicting one year before failure. Then, the model derived to obtain the probability of failure two years before bankruptcy. Derived model is called z-score which is overall index of the model [12],

Beaver (1966) obtained 14 financial ratios as significant indicators, then Deakin(1972) used same ratios to derive a linear model and to see which analysis gives the most effective outcome to predict the probability of failure for the next period. In his study, firstly dichotomous classification was employed with one difference that only bankrupted or insolvent firms have been chosen as failure. Furthermore, 32 failed firms were selected in the time period between 1964 and 1970. As a result of his first step of study, it is obtained that the data was not applicable to categorize the firm when the difference of error rates were significant. Then, MDA analysis was examined and it is seen that MDA classified the firms with 97%, 95.5% and 95.5% accuracy before three, two and one year before bankruptcy, respectively. However, Deakin (1972) examined the model to another sample consisting of 11 failed and 23 non-failed firms and the error terms of z-score were found 22%, 6%, 12%, 23%, and 15% five,four, three, two years and one year before failure, respectively. Therefore, he concluded that statistical analyses, especially MDA, could give significant and accurate prediction of failure, but it might be differed by type of sample and size of population [19].

Data set of previous studies was based on the matching of the number of firms for both failed and non-failed. However, Ohlson (1980) used the details of 105 bankrupt firms and 2,058 existed firms. Additionally, the data was taken from 10-K financial statements contrary to previous ones and this selection brought an advantage of transparency which means that one can check the specific time of a bankrupted firm. Some significant findings of the study for the factors to impact the probability of failure were considered as follows; measure of financial details, size of a firm, estimate of current liquidity and evaluation of the performances. Since there are some constraints to employ the MDA such as normality assumption of independent variables and sameness of the variance-covariance matrices, Ohlson (1980) introduce the conditional logit analysis to avoid those requirements. As a result of the study by using the logit analysis, three model have been examined in purpose to find the probability of failure for one, two and three years before bankruptcy and their correct predict percentages were 96.12%, 95.55% and 92.84% for one, two and three year before failure, respectively

[34].

Later, researchers focused on some complex models such as Probit Model and Hazard Model introduced by Zmijewski (1984) and Shumway (2001), respectively. Zmijewski (1984) examined the probit model by constructing the probability of failure as $P = \Phi(\beta^{'} X)$ where X is independent variables vector and $\Phi(.)$ is cumulative normal distribution function. Thus, the outcome would be in the range 0-1 because of using cumulative normal distribution function as a map. The research concentrated on two possible bias resulting from the selection of data which are choice-based sample and sample selection. By using Probit model to compare two assigned data with three financial ratios, with the choice-based sample, data were constructed according to the knowledge of dependent variable , however complete data were used in the examination of sample selection without any adjustment. As a result, it has been obtained that adjusted estimation methods(used in choice-based sample) acquired the population better [45].

Shumway (2001) argued that it is appropriate to include all detail of past years of a firm during its existence instead of taking each-firm year by using discrete time hazard model. Addition to financial ratios, market driven ratios have been applied to generate more accurate models against to single-period ones introduced before. By using Simple Hazard Model, it controls the risk of failure during the years contrary to single-time model, includes the time-varying covariates to let changeability of independent variables during their existing and has much more efficient usable information since it has includes all years of firms. $F(t_i, x_i)$ is the cumulative density function of $f(t_i, x_i; \theta)$ which is the probability of failure of company i at time t_i and θ is the coefficients of ,X, independent variables. y_i takes one if the firm i went bankruptcy or zero otherwise, in the maximum likelihood function of introduced model stated below [38];

$$L = \prod F(t_i, x_i; \theta)^{y_i}[1 - F(t_i, x_i; \theta)]^{1-y_i}) \tag{1.1}$$

In all earlier studies, both in linear and non-linear approaches, there are some constraints for the variables in order to enable them to use such as normality assumptions for the linear models. Therefore, transformation of the data has been focused on some researchers to manage the process. A related research done by Heijden (2011) concentrated on the analysis of some financial ratio used in insurance companies such as loss ratio, the combined ratio, the expense ratio and return on assets. In his study, he emphasized that lognormal and square root transformations did not work well compared to the usual normalisation process. Moreover, it was also found that after normalisation and transformation application, correlation between all ratio has been strength [42]

For the first time, a statistical early warning model was applied to Turkish insurance companies by Genc (2002). His study was comprised of three parts which are the financial analysis of insurance companies, an early warning model and the rating, respectively. First part includes the types of financial analyses applied to insurance companies and some ratio analyses and solvency applications to insurance sectors. Ratios related to measure the insurers were defined and obtained that their usage would be considered as an indicator of financial condition of a firm, even solely. Then, Some solvency applications exposed in USA and Europe were introduced and Solvency Margin (which is based on risk assessment) was examined to Turkish insurance companies to define capital adequacy as a part of the early warning model. In this method,value of factors were determined for the each of defined risk weighted assets. Then, each value of asset was multiplied with the related risk factor and sum to find the overall risk weighted assets of a firm. If the adjusted equity amount to total risk weighted asset ratio of the firm is over the 100% , then the company was considered as solvent. If it is between 50% and 100%,then the position of the company is warning, otherwise seen insolvent. As a result, Solvency Margin Ratio was found considerably significant indicator for the data of Turkish insurance sector. After, as a last part of the study, 22 firms including failed and non-failed have been employed to derive an early warning model from the financial statements of the firms acted in non- life branches in period of 1993-2004. Fourteen financial ratio were chosen regarding the ability of indicator of the firms' position and used in a linear model as independent variables. As a dependent variable, y, was taken 1 if the company still exist,or zero otherwise. Multiple regression by the help of MINTAB tool was employed by using stepwise method and as a result, accuracy of the obtained model with five ratios was found 71,4% [22].

Isseveroglu (2005) applied multi-dimensional statistical methods to predict the failures from the beginning time and to select the indicators/factors to insurance companies acted in non-life elementary branches in Turkey [25]. Then, Isseveroglu and Gucenme (2010) developed their earlier study by comparing three models which are multiple and logistic regression and MDA to measure the power of models in predicting the probability of failure of a firm in the next period. Details of 45 insurance companies were employed with the 17 independent variables as financial ratios in the time period 1992-2006. After obtaining the models, logit model was observed better than the rest regarding the ability of prediction of the failures/difficulties of companies. Then, all models were taken to prediction of performances of companies in 2007 by using the details of firms in 2003-2006. The obtained model with logit regression distinguished the firms with the accuracy of 100%, 93,3% and 82,2% one,two and three years before bankruptcy, respectively [23].

1.2 The Aim of the Study

The aim of this study is to construct an early warning model for the non-life insurance companies by using Turkish insurance sector data. An earlier study done by Genc (2006) is taken as the guiding literature to re-evaluate the existing situation based on recent development. The technical and financial balance sheets, income statements of companies in Turkish insurance sector are taken into account. In the selection of the model accuracy a differentiation grade on the failure or non-failure is implemented. The data set contains financial details of 41 companies and during 1998-2012. The ratios are chosen with respect to the liquidity, the profitability and the credibility criteria. As a methodology, Linear Regression, MDA, Logistic and Bayesian Regressions are used to examine financial failure, respectively. Furthermore, normalization process is applied to the data by using Box-Cox transformation to fulfil the normality assumption and the results are compared with each other to obtain the best predictor model.

In addition to earlier study done by Genc (2006), two more random variables are put in a model which are age and a dummy variable. The qualitative variable is defined according to the premium production of a firm.

The remainder of the thesis is organized as follows: Chapter 2 introduces the indicators of insurance companies and its importance and gives some idea of growing insurance sector in Turkey through years.In Chapter 3, empirical analyses based on the data collected from insurance companies and comparison of the earlier study done by Genc (2006) is mentioned. Lastly, Chapter 4 discusses results of the study and some comments for future researches.

CHAPTER 2

SOLVENCY INDICATORS OF THE INSURANCE SECTOR

2.1 Turkish Insurance Sector

Second half of the 19th century in 1870, in Great fire Pera in Beyoğlu, lots of buildings has damaged and burned and that was the trigger event for the development of insurance business.In that area, lots of luxurious goods which have been sold by non-Muslims had a market and their workplace had been suffered. Besides that Galata which has been considered as a financial center has been effected by the fire. Because of all, foreign insurance firms got into sector in Turkey. In 1872, there were three English insurance companies, Sun, Northern and North British, in 1875, La Fonciere French, insurance company started to act in Istanbul. Then, Ottoman Bank established Umum Osmanlı insurance company in 1892.

All insurance firms acting in Ottoman decided to specify the common fire tariff in 1900 and that was the first time of applying a tariff in Turkey. However, First Turkish insurance company and laws had a chance of existence in Republic period. In 1929, Milli Reasürans commenced operation.Then, all insurance firms have been a part of the Ministry of Commence. With this development, some adjustments and regulations has been continued and some legal gaps have been tried to improve and fill.

In 1990, companies are allowed to price accident, engineering, fire and transportation insurance productions independently. With this law, the main aim is to provide efficient productivity in a competitive environment, to increase number of insured by extending logic of the insurance and to use collected incomes for development of nation effectively. However, the intention of spreading insurance awareness could not have reached the desired level.

After the earthquake in 1999, Natural Disasters Insurance Authority (DASK) has been incorporated and earthquake coverage has been made compulsory for all buildings. Moreover, travel insurance has been made obligatory for the agents in behalf of their passenger.

In 2001, with the acceptance of the individual pension savings and investment system law, life insurance firms started to acting separately. In 2005,in order to cover the risks of agricultural sector, TARSİM has been established and state-sanctioned agriculture insurance business has been started to do work. In 2006, an insurance pool was formed to standardize all acceptable risk, to transfer risks ideally, to pay all claims from the one and only center and to generalize the idea.

In 2007, old law on insurance control which didn't respond needs of current business was legislated away. With entering into force of the new law, works of harmonization code of the European Union have been accelerated and regulations have become more liberal. Furthermore,Insurance Information Center, TRAMER, SAGMER, HAYMER and HATMER have been established in branches of traffic, health, life insurance and chasing all claims, respectively. An ongoing study more than 10 years, Solvency II has been monitored closely. In 2009, with the release of EU regulations on this subject in our country, studies have been accelerated. In this context, Expertise Commission has been set up SEÇ 4 (QIS 4) and its trainings have been completed in 2010. With these studies, preparation of Solvency II and the knowledge level of the insurance companies has been step up [8].

On the other hand, the size of the business is still smaller compared to European countries' in Turkey. According to the OECD statistics published in 2004,while 249 firms in Italy and 105 firms in Greece were acting in business,just 47 firms operated in Turkey [2] . In 2014, this number increased to 68 that 39 of all act in non-life, 18 act in life/pension and 4 act in life insurance business(7 of all are not allowed to produce premiums). Here is the table of change in number of insurance companies during 1998-2013.

Table 2.1: Number of insurance companies acted during 1998-2013, http://www.hazine.gov.tr

Number of Companies	1998	1999	2000	2001	2002	2003	2004	2005
Total	63	62	64	64	55	47	47	45
Non-Life	24	23	27	27	21	15	15	14
Composite	17	17	13	13	13	12	12	11
Number of Life Comp.s	22	22	24	24	21	9	9	9
Pension						11	1	1
Life/ Pension							10	10

Number of Companies	2006	2007	2008	2009	2010	2011	2012	2013
Total	63	51	54	54	57	47	59	58
Non-Life	31	28	30	32	34	35	35	36
Life	13	11	10	9	7	7	6	6
Pension	11	11	13	13	16	17	17	18

While premium income in non- life branches was just 250 million dollars in 1985, it increased to about 20 billion dollars in 2013 in Turkey . In the mean time, size and reserve of the insurance sector increased in through years. Premium production of 2014 raised with 22% and reached to 24.1 billion TL. Among those, 20.7 billion TL were collected from the non-life branches and the rest were from life branches.

Table 2.2: Premium production and paid claim amounts of Turkish insurance sector by years, (Treasury, 2014), http://www.hazine.gov.tr

Years	Premium Production (TL)	Total Paid Losses (TL)
2008	10,203,150,662	5,575,590,236
2009	10,468,825,229	5,794,459,820
2010	11,940,388,555	6,205,981,132
2011	14,475,310,295	7,561,870,880
2012	16,791,724,964	8,624,210,507
2013	20,832,000,000	9,422,000,000

2.1.1 Effect on Economy

Development of insurance produced recovery in economy. By providing safely trading, transportation and credit insurances enhanced the market-shares of the corporates acting import and export businesses. Because, enterprises had the chance to get into different markets with guarantee when they had some problems caused by transportation. Besides that credit insurance created protection to finance business and this led to both increase in sale on credit and continuity of trading in market.

Funds, bonds, coupons, stocks and investment funds created by the collected premiums of insurance companies and that demonstrates the importance of assurance in economy. While the funds acquired from life business are turned to long-term investment, the funds contributed from non-life branches are made use of in short-term investments for the liquidity risk. Also, it should be stated that in Turkey, non-life business is more common than life insurance.

Insurance business is considered as a significant indicator of determining development level of all economies. And one of the critical criterion of social level of welfare is the growth of per capita income. Because, enlargement in savings by increasing of insurance funds support economic growth and improvement, it creates increment on domestic income. Therefore, it has an impact on raise on income per capita.

Premium production increased to 22% as of 31.12.2013 and the amount is about 24 billion TL. The balanced between premium income of life and non-life insurers stayed same and non-life business generated 86% of all production. The increase of premium production came from the branches of General accident, Motor third party liability, fire and earthquake insurances and engineering insurances [4].

2.1.2 Crisis Effect

1994 crisis effected insurance industry at a higher rate than the contraction of the economy. Deficiency caused by the crisis have been compensated in the next two years. Then, two earthquakes left its mark on economy in 1999. Estimated total loss of the events cost between 8 billion dollars and 30 billion dollars. Paid losses to the insured people has reached to 700 million dollars and most are covered by foreign reinsurers. After the earthquakes,earthquake insurance has become mandatory and Natural Disasters Insurances Authority has been established. In 2001 crisis, size of economy of Turkey decreased with nine percent and this also led to retro-sessions of personal demand on insurance and downsizing in reel sector. As a result of it, premium production and sum of assets were lowered in real values. Furthermore, it has brought on burden on companies. Some of them had the problems of insolvency and 17 firms went bankruptcy within two years. In spite of all unfavourable consequences of the crisis, all payables and benefits have been paid without support of Government, the expenses were meet by sources of Warranties and Guaranties Fund [7, 3].

By the end of 2008, while technical profitability of corporates declined with 13%, at the end of the period profits decreased with 75% for some. At the same growth rate of premium production was lower than the monetary depreciation and that caused to stagnation in growth of business. The main reason was that insurance operations were considered as additional costs. Effect of global crisis could be seen by viewing number of policies and it was detected that life insurance business was influenced more. This is because number of life insurance businesses assigned by banks in return for using credits which had reduction in that period declined. Although premium incomes were increased in 2008 and 2009, growing was still below the inflation rate. However, rate of growth in 2010 was above of the inflation rate and it went on incrementally [6].

2.2 Solvency Indicators

Capability of meeting the interests of insured people is the main concern of insurance companies. Therefore, they should satisfy both solvency and financial competency. Financial success is considered as the difference between assets and liabilities of the firm and it is also known as the equity of it. However, positive difference is not the only one indicator of the presenting firm's strength. Regarding regulations of this topic,solvency requirements, technical provisions, financial ratio analyses and conservation ratios are employed to control the ability of firms. The main aim of the regulations is to minimize the risk of default. An insurance company should meet all loss claims and expenses to ensure the financial solvency. Therefore, the result of the being insolvent arises from the short and illiquid assets. In other words, it depends on having sufficient technical provisions and capital required for the expenses and incurred claims [13, 22].

An accurate solvency capital is significant for an insurance company to carry out its business. At the same time, it is compulsory for the reputation of firm to sustain its existence [37]. Therefore, many countries has applied some specific regulations which differ from one to another related to their conditions of economies and these have been controlled by public scrutiny. In Turkey, Solvency regulations have been taken from the European Union System. According to the implementations used in the EU, equity which is considered as current solvency margin is determined by excess of loss subtracted from the total of paid-in capitals, contingency reserves, revolution funds and retained profits. And, required solvency capital is differ from life to non-life insurance businesses. For the non-life case, it is the higher amount which regarding premium and loss principles. In life business, it is the sum of outcomes related to liability and risk of insured people.

In Turkey, insurance companies employ some financial ratios which are published by Under secretariat of Treasury in the circular to control capability of financial positions. These ratios are categorized as solvency, liquidity, operating and profitability. These ratios are defined as follows [37] :

I) **Solvency Ratios**
   i) Premiums received/Equity
   ii) Equity/Total Assets
   iii) Equity/Technical Provision

II) **Liquidity Ratios**
   i) Liquid Assets/Total Assets
   ii) Liquidity Ratio
   iii) Current Ratio
   iv) Premium and Reinsurance Receivables/ Total Assets
   v) Agency Receivables/ Equity

III) **Operating Ratios**
   i) Retention Ratio
   ii) Compensation Ratio

IV) **Profitability Ratios**
   i) Loss Ratio(Gross)=Incurred Loss/Premiums Earned
   ii) Loss Ratio(Net)
   iii) Expense Ratio=(Sales+Service Expenses)/Premiums Earned
   iv) Combined Ratio
   v) Pretax Profit/ Premium Received
   vi) Profit(Gross)/ Premium Received
   vii) Technical Profit/ Premium Received

While computing the solvency ratios, it should be also taken into account the rates of equity to assets and technical provision, separately. When the assets and technical provisions of corporates are increased, equity capitals should be accrued evenly to protect stability of the financial positions. In other words, depending on premium production, capital of the firm should be in the same trend. Furthermore, computed high solvency ratio for a particular time means that the firm has an effective and enough reserve [37].

Because insurance companies are the financial intermediaries, quality of assets are significant to maintain to be solvent. A major part of assets of firms are invested in bonds, stocks and real estates. Proportion of these assets define the quality of assets of the firms and the power of bringing in money. When they are compared to banks, the advantage of the insurance companies is not to act in credit business. Assets should both be qualified to get enough returns and satisfy the cash demands [40].

Operations of insurance business have a great impact on their financial structures. Furthermore, being insolvent to insured people is the result of making wrong decision in operational business. Pricing, retention,choice of reinsurance, cash proceeds and dividend polices are considered as the most important factors that those effect not only operational business but also financial strength of corporates.

Profitability is regarded as one of the important components from the point of solvency. Profit is not just used to support equity by retained earnings, also a profitable corporate may have an efficient equity with the way of increase of capital.It is difficult to be sustainable position in business for a company that does not have any profit and an enough profitability ratio.

Indicators which are not included above categorization are listed below [1] :

i) Net Income Ratio:Insurance premiums are equivalent to total sales in the sector. The net income ratio is calculated by dividing net income by the total of earned premiums for a given period. It measures the effectiveness of the company at generating profits with each dollar of earned premium. A net income ratio of 10 % is worse than a net income ratio of 20%. The latter is 10% more efficient at creating net income out of earned insurance premiums and is considered more profitable.

ii) Policy Sales Growth: Policy is the vehicle by which a sale is made. Policies are equivalent to units or volume, and in the world of business, the more units you sell, the higher your net income will be. Policy sales growth looks at trends in policy sales over time. It is calculated by dividing the difference between the current period's sales revenue and the previous period's sales revenue, and then dividing that difference by the previous period's sales revenue. Higher policy growth equals higher sales.

iii) Percentage of Sales and Quotas-to-Production: The percentage of sales growth measures the percentage of policy renewals over a certain period time, and is calculated by dividing renewals by policies sold. The number can be based on the number of new clients or the number of new policies sold. This is an ideal Key Performance Indicator for measuring sales targets. Quotas-to-production measures how effective agents are at meeting sales targets. It is calculated by dividing total quoted business by total revenue for a given period.

iv) Claims Ratio and Time-to-Settle: The claims ratio is an insurance KPI that measures how well your sales are covering the cost of claims. It is calculated by dividing total claims per period by the total earned premium per period. The average time to settle a claim can be used in conjunction with the claims ratio. It is calculated by dividing the total number of days taken to settle a claim by the total claim. A high time to settle and a high claims ratio is cause for concern.

Moreover, premium production is a strong indicator to measure position of a company and to present the contribution of the insurance sector to any economy. Generally, companies consider the ratios related to loss. Because, it is important that having loss ratios under 0.25 which means that losses and costs are reasonably lower than premium income. Furthermore,it should be considered that how much percentage of equity could compensate the total payables in case the firm stops operations. If the percentage is lower than 0.50, the company sustains its business efficiently [13].

As it is mentioned in introduction chapter, there are various ways of examining financial distress. Since ratio analysis is a static examiner which means that it just shows the moment of firm, it does not reflect the changes which may incur in the future. However, using Turkish insurance data which reflects 14 years and 41 firms, continuous time models are not applicable for these type of shortfall data.

2.2.1 Solvency II Directive and Requirements

Solvency is known as a capability of a firm to maintain its business in long-term while meeting all obligations. In insurance sector, it is defined by having enough equity to carry on operations and meeting liabilities. Therefore, regulations and laws are employed in order to keep the consistency of economics in this respect [9]. In Europe, in order to asses the solvency of companies and create the common market, the Directive was firstly introduced called Solvency I in 1973. Then, it was changed to take into account the its gaps and established as Solvency II in 2007. These gaps are considered as low risk assessments, weak capability of meeting the claims of insured, problems of creating the common market and incompatibility of International Markets [43].

Basically, it is a regulatory framework of determining the capability of financially being solvent of an insurance or reinsurance company in respect of ability to compensate claims of insured people. The aim of the system is to maintain the operations of the companies or to carry their business on especially in case of financially distress periods. [30].

Solvency II Directive mainly concerns the risks of underwriting (insurance), market, credibility, operational and liquidity risks apart from regulation and audit parts [27]. Underwriting risk is measured by dividing written premium to technical reserve of each firm and it determines risk of the insurer by issuing policies. And, market risk considers the financial assets of the company and its investment incomes. One of the critical ones, credibility risk, is the risk of taking company's debit from agencies and reinsurer partners. [36]. Then, operational risk which is differently compared to other risks takes into consideration of internal management of the company. Lastly, liquidity risk is about liquid asset position of the company [20]. The Directive consists of three pillars and all above mentioned risk assessments are included in first Pillar. Pillar I consist of quantitative measurements, applied model and its validation and calculation of capital requirements which are Solvency Capital Requirement (SCR) and Minimum Capital Requirement(MCR). Pillar II requires well-structured internal audit, strong risk management skill of the insurers in undertaking their own risks and corporate governance. And Pillar III which is the final step of the Directive indicates the reporting of the firm to external auditors and transparency to public [5].

In Pillar I, risk based economic model is constructed by taking into account of total balance sheet approach, risk diversification, mitigation and absorption capacity of liabilities. Total balance sheet approach is determined as taking all assets and liabilities of the company in the light of their market values. Since as it is know that all types of risks do not occur at the same time. Therefore, companies should not be required to hold capital for all realizable risk and it bases on the diversification risk. By having different kind of risk, the insurer decrease to have the probability of having considerable amount of claims at the same time. Risk mitigation is generally considered as the spreading of the risk to the other companies with the way of reinsurance and co-insurance [9].

SCR is the target capital which helps to meet unexpected significant amount of loss and also brings the confidence to fulfill the claim of the insureds. While SCR is the higher amount, MCR is the applicable lowest capital. It could be calculated either by using standard formula which will be defined European Commission or by defining the internal formula which is confirmed by the Auditor Committee [5]. SCR calculation employs the Value-at-Risk(VaR) method by using one-year related equity amounts in 99.5% confidence interval. In that calculation, at least five risks listed below should be used in VaR, separately and those risks are evaluated by using risk premiums, paid loss amounts and reserve risks [16].

i) Non-life insurance risk

ii) Life insurance risk

iii) Health insurance risk

iv) Credit risk

v) Operational risk

Since all mentioned risks in Solvency II Directive focuses on the available financial details of the firm, it also includes the static analysis addition to stochastic approach by calculation of SCR and MCR. Therefore, examination of this early warning model is also applied in the light of Solvency II Requirements with taking into account the above mentioned risk by using related financial ratios.

CHAPTER 3

EARLY WARNING MODEL

In Turkey, insurance companies weren't steady for a while and this caused lack of the applicable data. Therefore, in contrast to the generalized early warning examinations, failures in different years are assumed to occurred within the analysis year [23]. Moreover, some firms stopped premium productions one or two years ago before bankruptcy and their premium related ratios are taken one or zero value depending on the financial means of ratio(If it is loss ratio, then the value has taken 1 because its effect increases the probability of bankruptcy). For non-failed firms, their strongest year are used in the analysis. On the other hand, for the failures, their usable worst year is considered. Because of some structural changes in financial table during years and improved version of the data of some firms, some limitation adjustments represented in data Description are made.

A statistical early warning model has been used to predict companies' financial position by observing 41 insurance firms acting non-life branches during 1998-2012. Among all, 17 firms went bankruptcy and 24 firms still acts in the sector. The model is built with explanatory random variables and dummy dependent variable.The dummy variable indicates the existence of each firm. If the company is not bankrupted during the time period of 1998-2012, then it takes zero otherwise one. 14 financial ratios, one dummy variable which indicates the size of firm and years(age) of each firm are taken into account as independent variables. First, 14 Financial ratios examined by Genc(2006) are employed to compare the study and see the effects of time [22]. Furthermore, since the premium production of insurers is an important indicators regarding the condition of insurer, dummy independent related to premium production and age variables are added to investigate the effect of two factors to the final model. Then, Box-Cox transformation is applied to the ratios in order to meet the normality assumption of linear regression.

3.1 Data Description

In this analysis,

i) All financial statements of insurance companies acted in period of 1998-2012 are collected.

ii) 41 non-life insurance companies' income statements, balance sheets, technical provision and premium income statement are used to drive financial ratios

iii) Continuity of the companies are investigated and all merges and re brands are taken into account.

iv) If the company is not changed its name and not seen in next year annual report of Treasury, that company is considered as bankrupted.

v) It is assumed that since few number of bankrupted companies is available in time period of 1998-2012, all bankruptcies occurred in a year.

vi) Year selection of bankrupted firms to be used in the analysis is done according to below classification constraints;

   1) Generally, it is aimed to select the financial ratios of one-year before bankruptcy.
   2) Having loss ratio higher than one
   3) Having a significant deficit amount.
   4) If the firm stopped its premium production in some years, those years are not used because of not calculating the ratios of those years.
   5) Having high liability ratios which is higher than two.
   6) Having negative ratios.

vii) For non-failed companies, generally their available last years' financial ratios are used in the analysis (2011 and 2012).

Financial ratios and two additional variables employed in the examination are listed below:

$X_1 =$ Liquid Asset/Total Asset

$X_2 =$ Premium Collection Ratio

$X_3 =$ Net Premium Receivables(Insurance and Agency Op.s)/Total Asset

$X_4 =$ Loss/Premium

$X_5 =$ Profit/Paid Capital

$X_6 =$ Premium Production /Coverage

$X_7 =$ Payables on Reinsurance Op./Equity

$X_8 =$ iability(Short Term)/Liquid Asset

$X_9 =$ Total Reserve/Net Premium

$X_{10} =$ Total Reserve/Liquid Asset

$X_{11} =$ Technical Profit/Premium

$X_{12} =$ Total Income/Total Asset

$X_{13} =$ Total Payables(Long and Short Term)/Equity

$X_{14} =$ Reinsurance share/Gross Premium

$A =$ Age, years of firm

$S =$ If the company has a premium production higher than average premium production of related year $S = 1$, $S = 1$ otherwise.

$Y =$ Dependent Dummy Variable, $Y = 1$ if the firm went bankruptcy, $Y = 0$ otherwise

The dummy explanatory variable takes one if the firm's premium income is under the average of the premium income of the related year and zero otherwise. And, age which determines the years of the company actively in the sector starts from 1998.

Calculation of some ratios changes depending on the account years since structure of the tables have changed two or three times within time period. For example, for the calculation of liquid assets cash and cash equivalents (cash, bank and other accounts) and the financial assets and financial investment at insureds' risk accounts are considered. And investments from the life insurance business is subtracted from the that account in past years data since there were some companies issued both life and non-life insurance. Moreover, net premium receivables includes assets operated by insurance and reinsurance business such as Loans to insureds, operational doubtful receivables, deposits on insurance companies. For the calculation of loss ratio, reinsurance shares are subtracted from both loss and premium amounts also unearned premiums reserve and outstanding claim reserve are added. All ratios are derived from the annual financial and income statements report of each firm during the time period 1998-2012. Since non-life business is taken into account, generally dynamic ratios are used instead of long-term indicators such as investment ratios.

For the failed 17 firms, it is seen that their loss ratios generally higher than one, premium collection ratios are lower than average, ratios related to profit is extremely low or negative and liability to liquid asset ratios are more than two. Furthermore, they didn't have consistency in their acting period. For the existence 24 firms, their strongest years are employed in the analysis. Trend analyses of companies which show their position with ratios presented in Appendix A with their reasons why it is selected as a failed or non-failed to be used in the examination. Because linear regression methods are used and normality assumption should be met, all ratios are tested in SPSS to check the distribution properties and they are considered separately. However, Box-Cox transformation is applied to all without considering even some of them already are normally distributed. Descriptive statistic of X_1 of each company is stated below table (3.1). As it seen that, some firms have just three years and Kolmogrov p-value couldn't be calculated. However, lots of them have p-values which are higher than 0.05 and they are found normally distributed.

Table 3.1: Descriptives of X_1 over year

Company	n	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis	Kolmogrov Stat.s	Sig.	Status
c1	9	0.3377	0.2022	0.1370	0.781319	1.6199	2.2945	0.2955	0.0226	Failed
c2	7	0.3161	0.1955	0.1598	0.7358	2.1155	4.7847	0.3077	0.044	Failed
c3	9	0.3002	0.0270	0.1702	0.4093	-0,4099	-1.0716	0.1603	0.200	Failed
c4	5	0.3090	0.0497	0.2261	0.4703	0.9529	-1.3384	0.3489	0.0460	Failed
c5	11	0.3260	0.0265	0.1045	0.4412	-1.5452	3.8846	0.2210	0.1390	Failed
c6	3	0.3050	0.0486	0.2147	0.3815	-0.7173	-	0.2317	-	Failed
c7	6	0.1728	0.0145	0.1275	0.2051	-0.3007	-2.570	0.2942	0.1138	Failed
c8	9	0.6993	0.0915	0.1904	0.9841	-0.9562	-0.0644	0.1621	0.2000	Failed
c9	9	0.7481	0.0928	0.0741	0.9660	-2.1094	4,8888	0.2914	0.0270	Failed
c10	9	0.4352	0.0552	0.0970	0.6168	-1.1976	0.8092	0.2930	0.0249	Failed
c11	6	0.1679	0.0197	0.0982	0.2236	-0.2418	-1.1471	0.1741	0.2000	Failed
c12	13	0.5328	0.0646	0.1295	0.8815	-0.2490	-0.7862	0.1562	0.2000	Failed
c13	3	0.2916	0.1104	0.0814	0.4558	-0.0178	-	0.2615	-	Failed
c14	5	0.4077	0.1092	0.0374	0.6646	-0.8228	0.4745	0.1888	0.2000	Failed
c15	2	0.4066	0.0810	0.3256	0.4876	-	-	0.260	-	Failed
c16	15	0.5192	0.0535	0.2926	0.8789	0.4461	-1.4101	0.1884	0.1587	Failed
c17	7	0.3165	0.1958	0.1601	0.7458	2.1164	4.7799	0.3100	0.039	Failed
c18	4	0.6916	0.1003	0.4280	0.8563	-0.8828	-1.0918	0.2694	-	Active
c19	14	0.5508	0.0211	0.4043	0.6514	-0.5444	-1.0250	0.2276	0.0475	Active
c20	15	0.4119	0.0455	0.1121	0.6431	-0.2403	-1.5285	0.1973	0.1198	Active
c21	15	0.3744	0.0469	0.1052	0.6628	0.0714	-1.0190	0.1657	0.2000	Active
c22	15	0.5274	0.0115	0.4294	0.5888	-1.0469	1.1222	0.2490	0.0130	Active
c23	15	0.4239	0.0221	0.3117	0.5841	0.7168	-0.5561	0.1893	0.1537	Active
c24	15	0.4282	0.0212	0.2837	0.5335	-0.1655	-1.3621	0.1650	0.2000	Active
c25	15	0.5927	0.0241	0.3731	0.7677	-0.4502	1.4694	0.1633	0.2000	Active
c26	15	0.3964	0.19007	0.26	0.531	-1.397	1.473	0.290	0.004	Active
c27	15	0.5797	0.08676	0.52	0.643	-0.214	-0.183	0.195	0,129	Active
c28	15	0.4437	0.19721	0.300	0.585	2.328	6.662	0.269	0.005	Active
c29	15	0.4604	0.39478	0.184	0.744	0.540	1.138	0.177	0.200	Active
c30	15	0.3710	0.01930	0.366	0.382	0.245	-1.447	0.164	0.200	Active
c31	15	0.2561	0.03578	0.233	0.285	0.004	-1.711	0.206	0.087	Active
c32	15	0.1671	0.11307	0.092	0.254	0.443	-1.269	0.182	0.194	Active
c33	15	0.4518	0.12268	0.371	0.541	-0.387	2.297	0.193	0.139	Active
c34	15	0.3727	0.03253	0.356	0.402	0.044	-1530	0.157	0.200	Active
c35	15	0.6407	0.27669	0.455	0.841	0.088	-0.603	0.156	0.200	Active
c36	15	0.3902	0.23504	0.225	0.563	-0.331	0.476	0.099	0.200	Active
c37	15	0.1667	0.01259	0.163	0.182	0.529	-1.640	0.290	0.001	Active
c38	15	0.4763	0.34889	0.232	0.721	0.300	0.283	0.166	0.200	Active
c39	15	0.4053	0.07693	0.356	0.462	-0.333	-0.748	0.106	0.200	Active
c40	11	0.3401	0.06230	0.303	0.382	-0.893	-0.777	0.261	0.034	Active
c41	3	0.7155	0.05933	0.671	0.764	-1.368	-	0.302	-	Active

Below graphic is belong to C_{22} which still acts in the sector. The company has been in consistency from 2006 and financial ratios of 2011 year are taken to use in the analysis. Furthermore, in table(3.2), it is detected that there are correlation between some variables:

- between X_1 and X_9
- between X_2 and X_8
- between X_4 and X_8, X_{12}
- between X_5 and X_7, X_8, X_{11}, X_{12}
- between X_7 and X_8, X_9, X_{11}, X_{12}, X_{13}
- between X_8 and X_9, X_{11}, X_{12}, X_{13}

- between X_9 and X_{11}, X_{12}, X_{13}
- between X_{11} and X_{12}, X_{13}

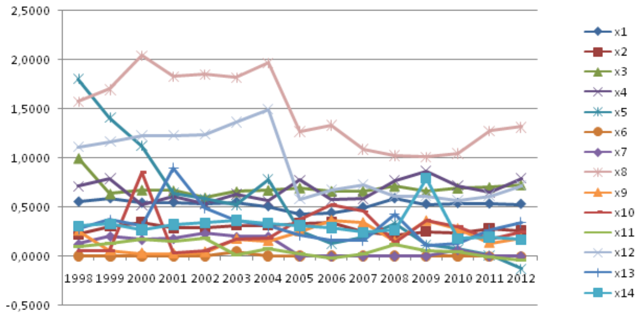

Figure 3.1: Financial ratios graphic of C_{22} by years

Table 3.2: Correlation Matrix of C_{22} of Financial Ratio

Correlations															
		X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
X1	Pearson Correlation	1	-.490	.114	.189	.412	.153	.423	.190	-.548*	-.456	.493	.324	.402	.011
	Sig. (2-tailed)		.064	.685	.499	.127	.586	.116	.498	.034	.088	.062	.239	.138	.969
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X2	Pearson Correlation	-.490	1	-.458	-.451	.076	.195	.329	.579*	-.258	.389	.037	.367	.063	.002
	Sig. (2-tailed)	.064		.086	.091	.788	.487	.232	.024	.354	.152	.896	.178	.824	.994
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X3	Pearson Correlation	.114	-.458	1	.225	.455	-.130	-.145	-.101	.231	-.189	-.095	-.048	-.116	-.161
	Sig. (2-tailed)	.685	.086		.420	.088	.643	.607	.719	.407	.500	.735	.866	.680	.567
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X4	Pearson Correlation	.189	-.451	.225	1	-.143	-.122	-.455	-.605*	.310	-.259	-.283	-.529*	-.243	.337
	Sig. (2-tailed)	.499	.091	.420		.611	.664	.088	.017	.260	.352	.306	.043	.383	.219
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X5	Pearson Correlation	.412	.076	.455	-.143	1	.013	.666**	.619*	-.400	-.187	.626*	.665**	.248	.041
	Sig. (2-tailed)	.127	.788	.088	.611		.962	.007	.014	.139	.505	.013	.007	.373	.884
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X6	Pearson Correlation	.153	.195	-.130	-.122	.013	1	.309	.262	-.041	-.097	-.172	.363	.082	.080
	Sig. (2-tailed)	.586	.487	.643	.664	.962		.263	.346	.885	.730	.539	.183	.771	.778
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X7	Pearson Correlation	.423	.329	-.145	-.455	.666**	.309	1	.892**	-.688**	-.304	.677**	.934**	.528*	.036
	Sig. (2-tailed)	.116	.232	.607	.088	.007	.263		.000	.005	.271	.006	.000	.043	.900
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X8	Pearson Correlation	.190	.579*	-.101	-.605*	.619*	.262	.892**	1	-.710**	-.068	.557*	.938**	.529*	-.060
	Sig. (2-tailed)	.498	.024	.719	.017	.014	.346	.000		.003	.810	.031	.000	.043	.831
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X9	Pearson Correlation	-.548*	-.258	.231	.310	-.400	-.041	-.688**	-.710**	1	.274	-.678**	-.609*	-.749**	.253
	Sig. (2-tailed)	.034	.354	.407	.260	.139	.885	.005	.003		.322	.005	.016	.001	.364
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X10	Pearson Correlation	-.456	.389	-.189	-.259	-.187	-.097	-.304	-.068	.274	1	-.118	-.233	-.497	.004
	Sig. (2-tailed)	.088	.152	.500	.352	.505	.730	.271	.810	.322		.675	.403	.059	.989
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X11	Pearson Correlation	.493	.037	-.095	-.283	.626*	-.172	.677**	.557*	-.678**	-,118	1	.553*	.549*	.157
	Sig. (2-tailed)	.062	.896	.735	.306	.013	.539	.006	.031	.005	.675		.033	.034	.577
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X12	Pearson Correlation	.324	.367	-.048	-.529*	.665**	.363	.934**	.938**	-.609*	-.233	.553*	1	.511	.048
	Sig. (2-tailed)	.239	.178	.866	.043	.007	.183	.000	.000	.016	.403	.033		.052	.864
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X13	Pearson Correlation	.402	.063	-.116	-.243	.248	.082	.528*	.529*	-.749**	-.497	.549*	.511	1	-.124
	Sig. (2-tailed)	.138	.824	.680	.383	.373	.771	.043	.043	.001	.059	.034	.052		.660
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
X14	Pearson Correlation	.011	.002	-.161	.337	.041	.080	.036	-.060	.253	.004	.157	.048	-.124	1
	Sig. (2-tailed)	.969	.994	.567	.219	.884	.778	.900	.831	.364	.989	.577	.864	.660	
	N	15	15	15	15	15	15	15	15	15	15	15	15	15	15
* Correlation is significant at the 0.05 level (2-tailed).															
** Correlation is significant at the 0.01 level (2-tailed).															

Below figure(3.2) belongs to the company C_1 which went bankruptcy at the en of 2006. In 2005 and 2006, no premium income were stated in its financial statements. In 2004, the firm had 0.91 loss ratio, 3.04 STL/LA, negative profit, etc. Therefore, 2004 year of financial ratios are used in the analysis both considering classification constraints and applicable year close to bankruptcy.

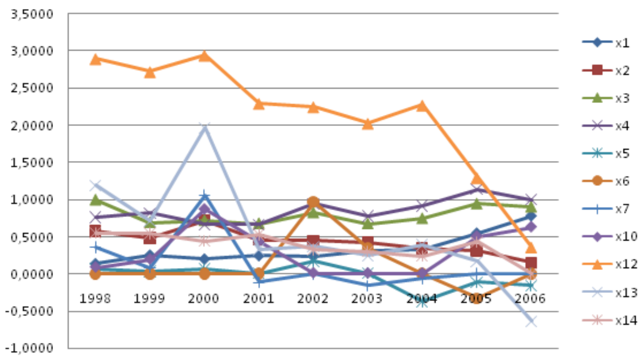

Figure 3.2: Financial ratios graphic of C_1 by years

3.1.1 Box-Cox Transformation

The Box-Cox transformation (Box & Cox, 1964) represents a family of power transformations that incorporates and extends the traditional options to help researchers to find the optimal normalizing transformation for each variable. As such, Box-Cox represents a potential best practice where normalizing data or equalizing variance is desired. Power transformations are merely transformations that raise numbers to an exponent. Therefore,a potential continuum of transformations could provide a range of opportunities for closely calibrating a transformation to the needs of the data [35]. Therefore, in this study, by using SPSS Box-Cox transformation is employed due to the fact that it selects the best alternative transformation for each variable.

3.2 Empirical Analysis

Four methods which are Linear Regression, MDA, Logistic and Bayesian Regressions have been employed to analyse the ratios, respectively. Firstly, Linear regression is utilized and MDA is taken into consideration both to distinguish the significant variables should be in the model and to check accuracy of the results of linear regression. Then, it is found that MDA and Stepwise Linear Regression gave the same explanatory variables as significant. Selected variables then used in logistic and Bayesian regression and all their coefficients are compared also their R^2 values as discriminator factors to choose the best predictor model. These procedure is done before and after adding the dummy and age explanatory variables for transformed data. Lastly, by using data of 2005-2012, prediction is done with the selected model for the years between 2006-2013. The examination results are categorized regarding the confidence interval of related year.

3.2.1 Linear Regression

Linear regression is utilized to define the relation between independent explanatory variables and dependent variable. Moreover, the compatibility of the model to data is computed by looking the F-test statistic and R^2 values. In this study, linear regression is used to investigate the relation between explanatory random variables and categorical dependent variable which represents one if the firm is bankrupted and zero otherwise. To predict the probability of failure, it is assumed that if the predicted dependent variable is above the confidence interval, then the company is considered as poor in that account year. General form of linear regression function is stated below [33]:

$$Y = a_0 + a_1X_1 + a_2X_2 + ... + a_nX_n \tag{3.1}$$

a_0 is constant of the model, $a_i, i = 1, ..., n$ are the coefficients of each variable and Y is the dependent variable. Coefficient of the variables are predicted with incorporation of Ordinary Least Square Estimation. There are four mainly assumptions to use the linear regression as a predictor model: Linearity and Additivity, Statistical Independence, homoscedasticity and Normality [21]. In this study, Box-Cox transformation is applied to avoid the non-normality and it is seen that the model after transformation is more accurate to catch the bankrupted firms. In the analysis data, 41 firms have been examined to obtain the probability of being failure.

First analysis is done with transformed data which includes 14 financial ratios by using stepwise Linear Regression and obtained model is stated below:

$$\begin{aligned} \hat{Y} = 0.415 + 0.209X_4 - 0.216X_5 + 0.212X_7 + \\ 0.06X_8 + 0.09X_{10} - 0.109X_{11} + 0.158X_{12} - 0.218X_{13} \end{aligned} \tag{3.2}$$

(3.3)

Table 3.3: Linear regression result of data including 14 financial ratios

Variable Name	Coefficient Value	Standard Error	T-test statistics	Sig.
Constant	0.415	.113	-2.773	.009
Loss Ratio	.443	.209	2.525	.000
Profit/Paid Capital	-.216	.061	-3.077	.004
PoRO/Equity	.212	.077	2.993	.005
STL/LA	.006	.055	5.268	.003
TR/LA	.009	.053	4.693	.000
TP/Premium	-.109	.042	-2.640	.000
TI/TA	.153	.077	2.993	.005
TI/TA	-.218	.175	5.525	.016

All p-valeus of independent variables stated in table (3.3) were found significant with accuracy of 78.2% ($R^2 = 85.9\%$). Furthermore, coefficients are also logical such as

X_5, loss ratio, has a positive effect on predicting the probability of bankruptcy since it increases it when it is high. Then, age and dummy variable are added in to the analysis and the below model is obtained with $R^2 = 90\%$ of which variables significances is presented below table (3.4):

$$\hat{Y}_A = 1.035 + 0.231X_4 - 0.098X_5 + 0.13X_8 + 0.066X_{10} - 0.137X_{13} - 0.057A \tag{3.4}$$

Table 3.4: Linear regression result of data with additional variables

Variable Name	Coefficient Value	Standard Error	t-Test Statistics	Sig.
Constant	1.035	.162	2.687	.011
Age	-.056	.008	-6.637	.000
Loss Ratio	.231	.108	7.065	.000
Profit/Paid Capital	0.098	.049	-3.900	.000
STL/LA	.13	.022	5.021	.000
TR/LA	-.066	.045	-3.515	.001
TP(SL)/Equity	-.173	.140	-2.758	.009
Age	-.057	.082	2.042	.049

Effect of age is seen significant for all models when included as a new variable. However, dummy variable related to premium production indicator is not detected in the stepwise analysis. The reason could be the inconsistency of the firms' condition during the years as it is mentioned before.

3.2.2 Multivariate Discriminant Analysis (MDA)

Discriminant analysis takes into account the multiple explanatory variables to catch the relation with categorical dependent variable by using the combination of the independent variables [39]. Discriminant Analysis is used to determine which variable(s) are the best predictors of failure.It is similar to linear regression however, MDA is mainly employed in case of categorical dependent variable such as the cases of migrant/non-migrant status, making a profit or not, paying a mortgage or renting for a house, etc... The below form of MDA equation is similar to linear regression [28, 12]:

$$Z = v_0 + v_1X_1 + ...v_nX_n \tag{3.5}$$

where

Z: Discriminant Function

v_i: Discriminant Coefficient, $i = 0, 1, ..., n$

X_i: Explanatory Variables, $i = 1, ..., n$

Discriminant coefficients are the same a_is of the linear regression which are unstandardised. The aim of this examination is to distinguish the cases into the related categories by maximizing the distance between groups. One less the number of categories equals to the number of discriminant function. Therefore, since there are two categories in this case, one discriminant function will be come up. Normality assumption holds for MDA as well as Linear regression. Moreover,it is important that classification of the groups of variables should be correctly selected. Chi-square statistical test is utilized to seek prediction power of the model. The discriminant score is achieved by weighting the variables in a combination. As a result of the analysis, it is expected to find the best classified model and to decrease the probability of misclassification [26].

Classification is done according to the cut-off value of Z-score value. The cut-off value is computed as the mean value of centroids which are the average of value of each predicted group. After determination of the cut-off value, the discriminant scores below the cut-off are considered as non-failed, otherwise failed in this analysis [12]. SPSS is used as a statistical tool and data is arranged in the same way of linear regression.

First test is done with transferred 14 financial ratios and the obtained result in equation (3.6) includes the same random variable estimated in linear regression with different coefficients.

$$\hat{Y} = 0.582X_4 - 0.649X_5 + 0.623X_{10} - 0.688X_{11} + 1.374X_{12} \tag{3.6}$$

Table (3.5) and (3.6) are SPSS outputs of the above model. According to the table (3.6) all variables have p-values lower than 0.05 which means that all variables are found statistically significant. Their sign effect on dependent variable give also meaningful signals.

Table 3.5: Coefficients of the transformed data in the MDA analysis

Canonical Discriminant Function Coefficients	
	Function
	1
Loss Ratio	.582
Profit/Paid Capital	-.649
TR/LA	.623
TP/Premium	-.688
TI/TA	1.374
Constant	.000
Unstandardized Coefficients	

Table 3.6: P-values of the detected variables in MDA analysis

Variables Names	Exact F-Test Statistics			
	Statistics	df1	df2	df3
TI/TA	34.875	1	39.000	.000
TP/Premium	26.975	2	38.000	.000
TR/LA	23.386	3	37.000	.000
Profit/Paid Capital	22.063	4	36.000	.000
Loss Ratio	21.562	5	35.000	.000

Table (3.7) represents the strong predicting power of the model which indicates the difference between failed and non-failed firms. The obtained model distinguishes the group accurately with 97.6% accuracy.

Table 3.7: Classification accuracy of the MDA model including 14 financial ratios

Counting Type			Predicted Group Membership		Total
			.00	1.00	
Original	Count	.00	24	0	24
		1.00	1	16	17
	%	.00	100.0	0.0	100.0
		1.00	5.9	94.1	100.0
Cross-validated	Count	.00	24	0	24
		1.00	4	13	17
	%	.00	100.0	.0	100.0
		1.00	23.5	76.5	100.0
a. 97.6 of original grouped cases correctly classified.					
b. 90.2% of cross-validated grouped cases correctly classified.					

As mentioned before, cut-off value to be used in the classification is calculated by taking average of group centroids. Since centroid of bankrupted firms is -1.441 and acting firm is 2.034 in table(3.8), then the cut-off value of the model is 0.296.

Table 3.8: Group centroids of the each group applied to transformed data in the MDA analysis

Functions at Group Centroids	
Dependent Variable	Function
	1
.00	-1.441
1.00	2.034
Unstandardized canonical discriminant functions evaluated at group means	

In table (3.9), R^2, determination of coefficient is found as 75.5 by using Wilk's Lambda.

Table 3.9: Test of determination of the coefficients applied to transformed data in MDA analysis

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.245	51.325	5	.000

Then, as a next step, additional variables are added to the analysis and the below model is obtained. Since it is seen from table (3.11), all coefficients are found statistically significant.

$$\hat{Y}_A = -3.938 - 1.411X_4 + 0.936X_5 - 0.714X_7 - 1.228X_8 + 1.2X_{13} \\ +0.606X_{14} + 0.316Age \qquad (3.7)$$

Table 3.10: Coefficients of transformed data with additional variables in the MDA analysis

Canonical Discriminant Function Coefficients	
Loss Ratio	-1.411
Profit/ Paid Capital	0.936
PoRO/Equity	-0.714
STL/LA	-1.228
TI/TA	1.200
RS/GP	0.606
Age	0.361
(Constant)	-3.938

Effect of Age variable increases the determination of coefficient to 89.6% as seen in table (3.12)

However, all coefficients are significant, their effect on the results are not reasonable. For example, coefficient of loss ratio is expected as a positive value because it increases the probability of ruin when it is high, and in this case its value is negative even the prediction power is higher than previous one.

Table 3.11: Significance of coefficients in the MDA analysis including additional variables applied to transformed data

The Output of the Variables Kept in the Model									
Step	Entered	Wilks' Lambda							
		Statistic	df1	df2	df3	Exact F			
						Statistic	df1	df2	df3
1	Duration	.426	1	1	39.000	52.638	1	39.000	.000
2	Loss Ratio	.253	2	1	39.000	55.998	2	38.000	.000
3	Profit/Paid Capital	.205	3	1	39.000	47.974	3	37.000	.000
4	STL/LA	.175	4	1	39.000	42.475	4	36.000	.000
5	TP(LS)/Equity	.140	5	1	39.000	43.090	5	35.000	.000
6	RS/GP	.117	6	1	39.000	42.888	6	34.000	.000
7	PoRO/Equity	.104	7	1	39.000	40.786	7	33.000	.000
At each step, the variable that minimizes the overall Wilks' Lambda is entered.									
a Maximum number of steps is 32.									
b Minimum partial F to enter is 3.84.									
c Maximum partial F to remove is 2.71.									
d F level, tolerance, or VIN insufficient for further computation.									

Table 3.12: Test of determination of the coefficients applied to transformed data in MDA analysis including additional variables

Wilks' Lambda				
Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.104	80.483	7	.000

3.2.3 Logistic Regression

It is known that linear regression may not deal with the nominal dependent variable as much as scale data. Therefore, another approach to be dealt with the multiple independent variables and categorical dependent variable is to utilize the logistic regression as well as MDA [17]. It aims to maximize the probability of classification correctly by using log odds and odds ratio. It should be emphasized that since the aims of MDA, linear and logistic regressions are the same, however the assumptions are not strictly and ways of approaching the results are different. The main assumptions of logistic regression as follow [41]:

- it does not require linearity between dependent and independent variables
- it does not need the normality assumption of independent variables
- Larger samples are preferable, at least more than 50 observations

Since log and square root transformation are used to normalize the distribution, in logistic regression, log transformation is utilized to predict the probability of each category. This log transformation helps us to produce a link with linear regression.

Let's consider the data includes 100 observation and 60 of all belongs to group a and rest is in group b. Then probability of being category a is 60%. However, logistic regression method utilize the odds and then the probability is found by using odds in a opposite way. The odds is found by dividing the observation of cases as $60/40 = 1.5$. Then the probability, P, is computed as below:

$$P = \frac{\text{odds}}{\text{odds} + 1}$$

In our case, let's consider p as a probability of being in the group of failed firms and represent it as $p = P(Y = 1|X)$. Then, let $1 - p$ be the probability of being in the group of non-failed firms and shown as $1 - p = P(Y = 0|X)$. The odds of failed and non-failed are founds as below [41]:

$$\text{odds(failed)} = \frac{P(Y = 1|X)}{1 - P(Y = 1|X)}$$

$$\text{odds(non-failed)} = \frac{P(Y = 0|X)}{1 - P(Y = 0|X)} = \frac{P(Y = 0|X)}{P(Y = 1|X)}$$

Then, let's take the log transformation of the odds and write the form of linear regression as follows [41]:

$$ln(\frac{p}{1-p}) = c_0 + c_1X_1 + ... + c_nX_n \tag{3.8}$$

and

$$P(Y = 1|X) = \frac{1}{1 + exp(-c_0 - c_1X_1 - ... - c_nX_n)}$$
$$P(Y = 0|X) = \frac{exp(-c_0 - c_1X_1 - ... - c_nX_n}{1 + exp(-c_0 - c_1X_1 - ... - c_nX_n)}$$

where

$c_0 =$ constant

$c_i =$ logistic coefficients from $i = 1, ..., n$

As it is seen above equations that the probability is not the linear combination of the explanatory variables, however by using log transformation as in equation (3.8), it turns out the normal linear regression.

In contrary to MDA and Multiple Linear Regression, Maximum likelihood function is utilized in Logistic Regression. It also aims to avoid the homoscedasticity and normality assumption criteria. It is still aimed to minimize the residuals to produce the logit coefficients by adapting the maximum likelihood [24]. SPSS program is again used as a tool with the stepwise option of binary regression. First analysis considers

14 financial ratios and categorical dependent variable. Table B.01 is used to compare the model which only includes the constant with the model of consisting explanatory variables. It gave the 58.5% accuracy of prediction while just the constant is in the model.

Omnibus test uses the chi-square results to determine the significance of the model when the explanatory variables are added.(table in 3.13). It gives the answer of the hypothesis test below:

H_0= The model is significant with the constant

H_1= The model is significant with the predictors

Since the p-values of three steps are lower than 0.05, the null hypothesis is rejected. It means that after adding the predictors to the analysis, the model with the detected variables as a good fitting model. It should be emphasized that in every step, the model becomes better regarding the prediction power and in this analysis three steps occurred.

Table 3.13: Significance test of logistic regression

Omnibus Tests of Model Coefficients				
		Square	df	Sig.
Step 1	Step	24.468	1	0.000
	Block	24.468	1	0.000
	Model	24.468	1	0.000
Step 2	Step	16.700	1	0.000
	Block	41.167	2	0.000
	Model	41.167	2	0.000
Step 3	Step	14.470	1	0.000
	Block	55.637	3	0.000
	Model	55.637	3	0.000

In model summary table (table 3.14), 74.3% of the variation in the categorical dependent variable is explained by the logistic model. It could be considered as R^2 like in Multiple Linear Regression results, however it does not fulfil it completely. On the other hand, Nagelkerke R^2 shows the strong relationship between the predictors and prediction with 100%.

An alternative of chi-square is Hosmer and Lemeshow test. It gives the answer of below hypothesises:

H_0= There is no difference between observed and predicted model values

H_1= There is a difference between observed and predicted model value

To obtain a well-fitted model, it is desired to fail to reject the null hypothesis as seen in this analysis(table B.3 in Appendix B). Since the p-value of step 3 is greater than the 0.05, it is also seen in this result that the obtained model is well-fitted.

Table 3.14: Explanation power of the logistic model

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	31.169 a	0.449	0.605
2	14.470 b	0.643	0.853
3	0.000 c	0.743	1.000
a. Estimatiom terminated at iteration number 6 because parameter estimates changed by less than .001			
b. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001			
c. Estimation terminated at iteration number 24 because a perfect fit is detected. This solution is not unique.			

Table (B.4) in Appendix B, classification of the categories are presented in the examination. The examination divides the observations to 10 groups with three steps and related table is shown in Appendix B. According to appendix, the obtained model classified the non-failed,failed firms and overall prediction with 100%, 94.1% and 97.6% accuracy, respectively.

In Table (3.15), the coefficients of obtained variables and their Wald tests are presented to asses their significance after stepwise logistic regression. Second column is the predicted logistic coefficients of explanatory variables. They are used to define the probability of a case in the equation 3.11. Furthermore, it is seen that in step two X_{12} is not significant according to the p-value of 0.092 which is greater than 0.05.

Table 3.15: Coefficients of variables in the logistic model

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1,a	TI/TA	2.514	0.899	7.826	1	0.005	12.359
	Constant	-2.884	0.823	12.280	1	0.000	0.056
Step 2,b	Loss Ratio	15.760	6.304	6.250	1	0.012	6992632.310
	TI/TA	4.796	2.842	2.846	1	0.092	120.869
	Constant	-15.624	6.091	6.579	1	0.010	0.000
a. Variable(s) entered on step 1 : TI/TA							
b. Variable(s) entered on step 2 : Loss Ratio							

The analysis is followed with the additional explanatory variables which are age and the dummy variable related to premium production. Its results are quite similar with previous one. It is detected that X_4 and age variables are found in the third step but except age all their Wald significant values are greater than 0.05. Transformed data is not used in logistic regression due to the fact that normality assumption is not required.

3.2.4 Bayesian Regression

Until now, the examined regression models consider the coefficients, dependent and independent variables as fixed values. With the Bayesian approach, it is aimed to find the unknown coefficients by considering them as random variable with the fixed dependent and independent variables [32]. Since the coefficients are not fixed values, then firstly their prior distribution should be defined. These process is done by employing Gibss Sampling methods to generate random coefficients by using the prior mean and variance to get into the model. Also, it is assumed that the density of the prior is the multivariate normal.

As a starting point to Gibbs sampling, let,'s consider the general form of linear regression as stated below [29]:

$$Y = \beta_0 + \beta_1 X_1 + ... + \beta_n X_n + \varepsilon$$
$$\varepsilon \sim N(0, \sigma^2) \tag{3.9}$$

Since the parameters to be estimated in (3.11) are β and σ, there should be a prior density function,such as $f(\beta, \sigma) = f(\beta) * f(sigma)$ to assign them.$f(\beta) \sim N(q, Q))$ and $f(\sigma) \sim Gamma(1/\sigma)$ For this assignment, mean and variance of these parameters are needed. With the help of following likelihood function of Bayesian methodology, mean and variance of the posterior,β, is derived as follows [11]:

$$L(\beta, \sigma) \propto (1/\sigma^n) exp((Y - X\beta)^{'}(Y - X\beta)/2\sigma^2) \tag{3.10}$$
$$f(\beta, \sigma) \propto (1/\sigma^{n+1}) exp((\beta - \hat{\beta}(\sigma))^{'}(V(\sigma))^{-1}(Y - X\beta)/2\sigma^2) \tag{3.11}$$
$$\hat{\beta}(\sigma) = (X\acute{X} + \sigma^2 \acute{Q} Q)^{-1}(\acute{X}Y + \sigma^2 \acute{Q} q)$$
$$V(\sigma) = \sigma^2 (X\acute{X} + \sigma^2 \acute{Q} Q)^{-1}$$

where $\acute{\beta}(\sigma)$ is mean of posterior in condition to the parameter σ and $V(\sigma)$ is the variance of it. Then, σ^2 is replaced with the estimated value of itself which is $\hat{\sigma}^2 = (Y - X\hat{\beta})^{'}(Y - X\hat{\beta})/(n-k)$ based on least square estimate of $\hat{\beta}$. At that point, Gibbs Sampler Method simplifies the process with MATLAB program. The codes are stated below. The process starts with defining number of observation,n, and independent variables$k$. First, R kxk matrix is composed to create the variance, it is a unit matrix of which units are replaced with the prior variances of each explanatory variable taken from the stepwise linear regression. Then, bo is defined by using OLS as initial values. 'sige' is computed as an initial value of the estimated σ^2. The algorithm was repeated until reaching the ultimate β.

Coding stated in Appendix C belongs to the data consists of seven variables obtained in both MDA and Multiple Linear Regression. Then, this algorithm is also used for the transformed data. As a result, the coefficients are found with slightly different than the results of the linear regression.(table (3.16) and table(3.17))

Table 3.16: Bayesian regression result table of data including 14 financial ratio

Gibbs Estimates			
Variable	Coefficient	t-statistic	t-probability
Intercept	1.0351	22.4452	0.0000
Loss Ratio	0.2307	11.6172	0.0000
Profit/Paid Cap.	-0.0982	-4.5093	0.0000
STL/LA	0.1305	5.7281	0.0000
Tot. Resr./LA	0.0656	3.3024	0.0019
T. Pay(Long and Short Term)/Eq.	-0.1374	-6.5195	0.0000
Duration	-0.0569	-14.2862	0.0000
Theil - Goldoerger Regression Estimates			
R - Squared = 0.9034			
Rbar - Squared = 0.8864			
σ^2 = 0.0283			
Durbin - Watson = 1.8520			
Nobs, Nvars = 41, 7			
Variable	Prior Mean	Standard Deviation	
Intercept	1.035	0.0798	
Loss Ratio	0.231	0.0286	
Profit/Paid Cap.	-0.098	0.0328	
STL/LA	0.13	0.0349	
Tot. Resr./LA	0.066	0.0294	
T. Pay(Long and Short Term)/Eq.	-0.137	0.0314	
Duration	-0.057	0.0070	

3.3 Comparison of the Models and Warning Index

The prediction of each company's probability of bankruptcy has been applied for the time period 2006-2013. Since the models obtained by linear and Bayesian regressions are quite similar, below model was utilize to the prediction.

$$\begin{aligned}\hat{Y}_D = 1.035 + 0.231X_4 - 0.098X_5 + 0.13X_8 + \\ 0.066X_{10} - 0.137X_{13} - 0.057Duration\end{aligned}$$

According table (3.19), all bankrupted firms are captured and some warning cases have been seen. The prediction classification of the firms are presented in Appendix C.

In order to see the ability of capturing failed and existing companies, the above model is employed to check while applying it to the data of 2005-2012, separately. Predictor model detected all bankrupted firms during that period. In that point, as a threshold

Table 3.17: Bayesian regression result table of data with additional variables

Gibbs Estimates			
Variable	Coefficient	t-statistic	t-probability
Intercept	0.4356	4.9710	0.0000
Loss Ratio	0.7602	10.8765	0.0000
Profit/Paid Cap.	-0.1908	-5.9069	0.0000
Pay. on Reins Op./ Equity	0.1662	3.4816	0.0012
STL/LA	0.1110	7.5943	0.0000
T. Pay(Long and Short Term)/Eq.	-0.1573	-5.7466	0.0000
Reins. Share/ Gross Prem.	-0.3859	-4.1014	0.0002
Duration	-0.055733	-11.1077	0.0000
Theil - Goldoerger Regression Estimates			
R - Squared = 0.8964			
Rbar - Squared = 0.8744			
σ^2 = 0.0312			
Durbin - Watson = 2.6026			
Nobs, Nvars = 41, 8			
Variable	Prior Mean	Standard Deviation	
Intercept	0.434	0.1616	
Loss Ratio	0.761	0.1076	
Profit/Paid Cap.	-0.191	0.0490	
Pay. on Reins Op./ Equity	0.168	0.0820	
STL/LA	0.111	0.0221	
T. Pay(Long and Short Term)/Eq.	-0.158	0.044944	
Reins. Share/ Gross Prem.	-0.386	0.1399	
Duration	-0.056	0.0084	

value, the average of the each year results is defined and that value is assumed as a threshold value. The classification is done in three steps as follow:

i) If the result of a firm is lower than the threshold, it is categorized financially successful, (S)

ii) If the result of a firm is between the threshold and upper bound(at 85 % confidence level), it is categorized as warning, (W)

iii) If the result of a firm is higher than the upper bound, then it is categorized as insolvent, (I)

MDA has own cut-off value and categorization is done according to the rule that if the score higher than cut-off, then the firm is considered as insolvent. However, our aim is to evaluate probability of being insolvent instead of having strict outcomes. Therefore, MDA analysis was utilized to distinguish the meaningful variables in the analysis. In

Table 3.18: Comparison of the models

Variables	Box-Cox				
	Linear coef.	Genc coef.	MDA coef.	Logistic coef.	Bayesian coef.
LA/TA		1.09			
Net Premium Rec./TA		1.23			
Loss Ratio	0.231		-1.411	15.760	0.230
Profit/Paid Capital	-0.098		0.936		-0.098
PoRO/Equity		-0.036	-0.714		
STL/Equity	0.130		-1.228		0.131
TR/Net Premium		-0.141			
TR/LA	0.066	-0.483			0.065
TI/TA				4.796	
TP(LS)/Equity	0.137		1.200		-0.137
Reins. Share/GP			0.606		
D	-0.057		0.316		-0.056
Constant	1.035	1.310	-3.938	-15.624	1.035
R Square	90	78	100		90.3

Table 3.19: Warning Index of each year

	2006	2007	2008	2009	2010	2011	2012	2013
Mean	0.61	0.55	0.52	0.50	0.50	0.46	0.41	0.34
Std. Er.	0.20	0.30	0.36	0.33	0.36	0.27	0.40	0.34
Upper Lim.	0.81	0.84	0.88	0.83	0.86	0.72	0.81	0.63
I	>0.81	>0.84	>0.88	>0.82	>0.85	>0.72	>0.81	>0.63
W	0.61-0.81	0.55-0.84	0.52-0.88	0.49-0.82	0.50-0.85	0.46-0.72	0.41-0.81	0.34-0.68
S	<0.61	<0.55	<0.52	<0.50	<0.50	<0.46	<0.41	<0.34

addition to that Logistic regression model was not used to predict the probability of bankruptcy due to the fact that coefficients are not found significant in the analysis even the obtained model is detected as meaningful.

When all obtained ratios are taken into account to seek the contribution to the prediction outcome,separately, it is also seen that almost all effects of coefficients are logical;

i) Loss Ratio:Since its coefficient effect is positive and high values increases the credibility risk, it also increase the risk of bankruptcy.

ii) Profit/Paid Capital: Since higher profit decrease the probability of distress, its effect detected also lowering factor of the out come of the model,

iii) STL/LA: As all liability indicators enhance the insolvency, it effects the model in the same way.

iv) TR/LA: While reserve is the provision of the taken risk for the probable claims in the future, higher reserve amounts shows the wrong risk selection of the insurer. Therefore, its effect on the outcome of the model is considerable.

v) TP(LS)/Equity: It is known that equity is the main capital of the insurance company and it would not be desired to have close value of payables to it. Therefore, obtained model just in that case could not be considerable.

vi) D: If the company exists in the sector for a long time, it could be understood that company can maintain its business. So, its effect on the outcome is also meaningful.

Genc(2006) study obtained the below model to predict the probability of bankruptcy of the firms for 2005 .

$$\hat{Y} = 1.31 + 1.09X_1 + 1.23X_3 - 0.0356X_7 - 0.141X_9 - 0.483X_{10}$$

Contrast to this study, bankrupted firms took value of zero, acting ones otherwise in the empirical analysis done Genc (2006). Stepwise linear regression was employed with the help of Minitab program. In the prediction part, the above model detected 15 firms as insolvent for 2015 among 46 companies. Furthermore, categorization was done according to the cut value of 0.50, strictly [22].

It should be emphasized that X_{10} of obtained random variables was also detained by Genc(2006). In his study, bankrupted firms were assumed to take zero value and existence firms otherwise, just to opposite to obtained model of this study. Therefore, the common obtained ratio effect is in a same way even if their signs are different. Furthermore, if determination of the coefficients are compared, it is seen that explanation of the Bayesian model is higher that earlier study's one. The examination of Genc took into consideration of the data of 2004 year and he obtained 15 companies as insolvent. In this study, just two companies were detected as insolvent, seven companies determined as warning among all.

CHAPTER 4

CONCLUSION

In this thesis, it is aimed to obtain an early warning model for the Turkish insurance sector. As a starting point, guiding literature done by Genc(2006) is taken into consideration to replicate the study related to see the effect of time period and the changes of insurance market. In the examination, due to the limited number of companies, all failures in 1998-2012 are assumed to be occurred in a year and their applicable worst financial details are used. Furthermore, best years of the existing companies are taken to be investigated in the analysis. Firstly, all 14 ratios(as a replicating of Genc(2006)study) are utilized in a multiple stepwise linear regression. Although, prediction power of the obtained model is acceptable, since normality assumption is required, Box-Cox transformation is applied to explanatory variables and then application is repeated with the transform data. Then, two additional predictor are added to the data to be used in the analysis; duration of each firm and a dummy variable which indicates that a firm is under or above the yearly average premium production. With these two additional variables, analysis is done again both to pure and transformed data.

Then, MDA is utilized to compare the models as an alternative one because of its distinguisher future for selection of variables. The analysis is done with transformed data and additional variables, respectively. The obtained model found significant, however, coefficients effect on dependent variable is not meaningful. After MDA analysis, because of the property of the data Logistic regression is employed but not to transformed data. Again, the obtained model is significance. On the other hand, only three variables detected and both their effect to the dependent variable and significance values are not seen expressive. Lastly, Bayesian regression is used and chosen the best model among all with 90,2% of R^2.

Findings of the study could be listed as follows:

i) All companies had extreme values at least one time in their existence (Having significant amount of deficit, negative profits, liability ratios higher than one, etc.).

ii) It is seen that since changes of regulation during the time period, structures of financial tables and also some accounts are changed.

iii) While computing the used ratios, it is detected that all insurance companies had extreme values at least one time in their existence.

iv) Main problem arises from the lack of applicable data.

v) In company categorization part of the study, it is detected that expected consistency in each group is seen rarely.

vi) Guiding literature is improved as capturing all bankrupted firms with higher coefficient of determination.

vii) It is also seen that firms success is increased by years compared to guiding literature.

viii) The obtained model reflected all bankrupted companies in the prediction.

ix) Prediction categorization is done in confidence interval of 85% and categorization distinguished the firms accurately.

Contrubution of this study could be considered to examine the Bayesian Regression and add two variables compare to earlier study. It should be also emphasized that if avaliable data of the insurance sector had been used easily and reflected more accurately, the results would be more meaningful and another approaches would be examined.

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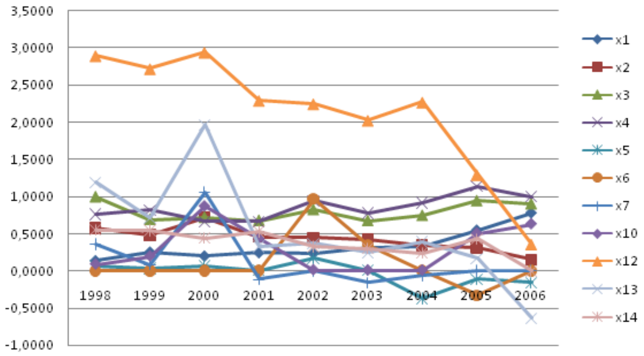
APPENDIX A

RATIOS OF EACH COMPANY BY YEAR

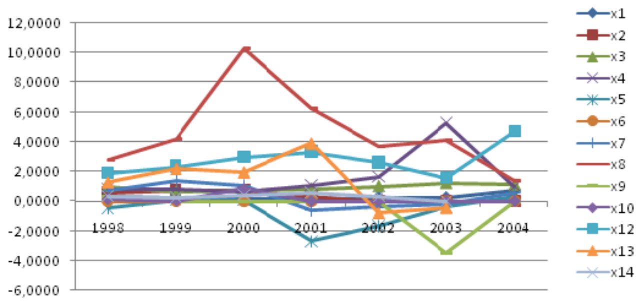
Bankrupted Companies

As it is known that it is expected to see the financial stability in accounting details of a firm to be regarded as successful. Therefore, in selection of analysis year of a firm, generally some measures are considered to make decision and it is also taken into consideration that selected years were chosen according to have up and down values of a firm. It should be emphasized that since they are ratios and should be in range of 0-1, selection of analysis data of each firm was done without taking extreme value of years, their most usable years of data were chosen. Generally, seen up and down ratios compared to average are utilized in selection of the year of firm. Also, high loss ratios are taken as the indicators of failure. Since premium production is an important sign of the insurer, ability of collecting premium is also considered. Furthermore, having valuable profit is a good sing and oppositely negative profit may lead to failure. Then, liability ratios are used also as indicators in the selection of firms.

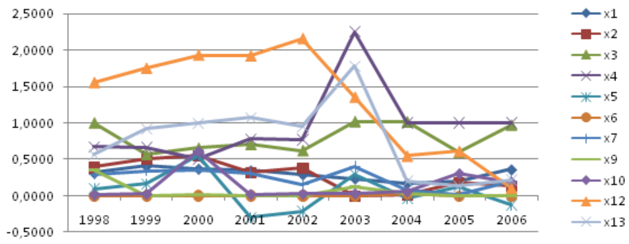
For C_1, as it is seen from below graphic, X_{13} and X_{12} are really high which seems unrealistic compared to stabilise companies. Also,since X_8, X_9 and X_{11} are seen extreme values, they are not included in order to catch the other ratios easily. Regarding upper and lower limits, ratios of 2004 year are chosen to employ in the analysis. For C_2, X_{11} ratio is not shown in the graph since its value of 2003 year is considerably high. 2001 is chosen as most usable data regarding bankruptcy criteria. For C_3, X_8, X_{11} and X_{14} were not shown in below graphic since they are so high because of having extreme values. 2006 year ratios are seen as most usable (lowest extreme value and applicable worst case to capture the bankruptcy).



(a) C_1



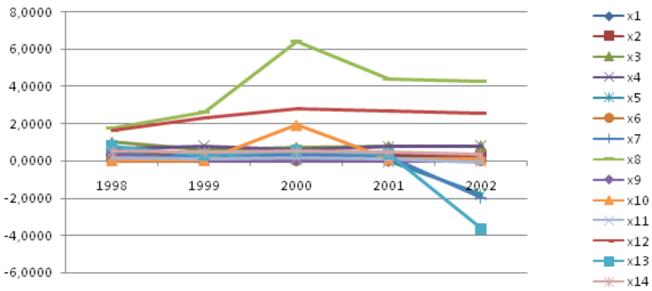
(b) C_3



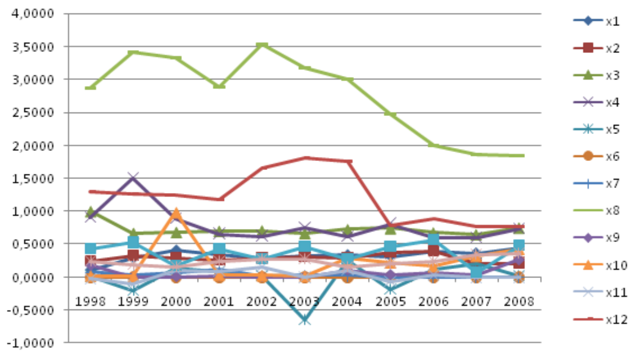
(c) C_3

Figure A.1: Financial indicators of the companies C_1-C_3

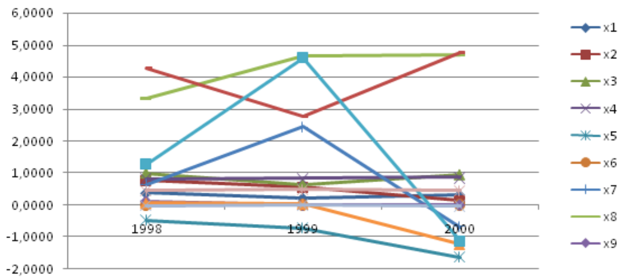
For C_4, as it is seen that, just 5 years could be used and 2001 ratios are detected to use in the analysis. For C_5, regarding up and down ratio values of years, 2003 year of data was chosen. For C_6, since our period of data starts from 1998 and given above details of company went bankruptcy in 2000, usable year is chosen as 1999 in the analysis.



(a) C_4



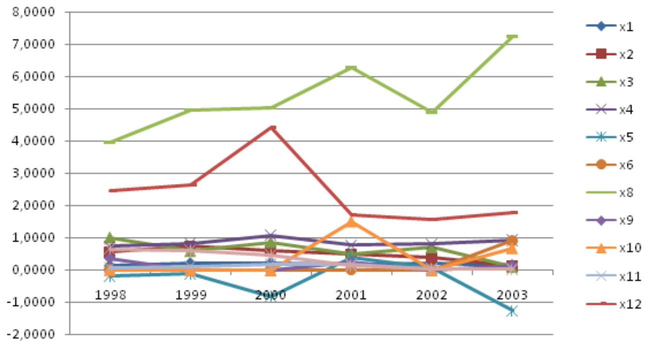
(b) C_5



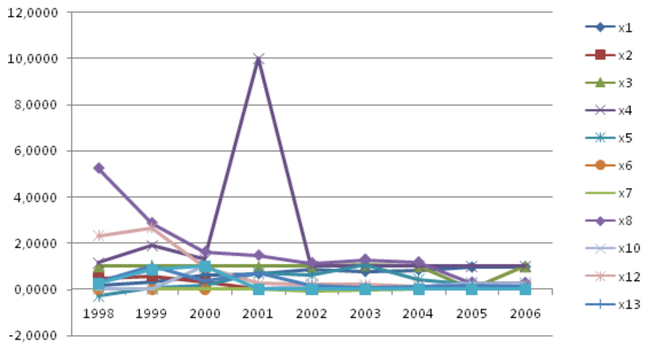
(c) C_6

Figure A.2: Financial indicators of the companies C_4-C_6

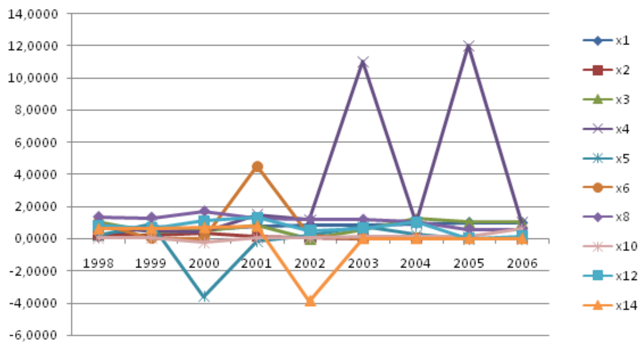
For C_7, X_{13} and X_7 are not included to graphic due to have very low and negative ratio values. Generally, high ratios related to liability and low ratios related to income are considered for selection and 1999 year was taken into analysis. For C_8, X_9 and X_{11} ratios have extremely high values, therefore they are excluded from the graphic. Since high and low ratios are seen a lot, most applicable year is chosen as 1999. For C_9, X_9, X_{11} and X_{13} are not shown in the graphic. 2000 year of company is chosen as an appropriate one in order to be used in the analysis since it reflects high loss ratio and liability ratios and low income ratios.



(a) C_7



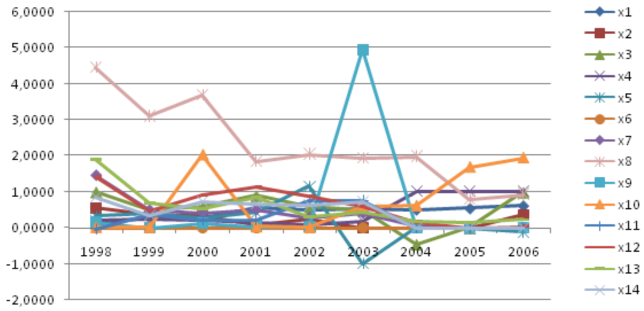
(b) C_8



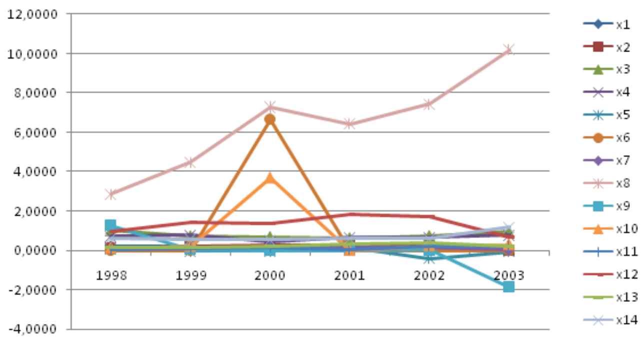
(c) C_9

Figure A.3: Financial indicators of the companies C_7-C_9

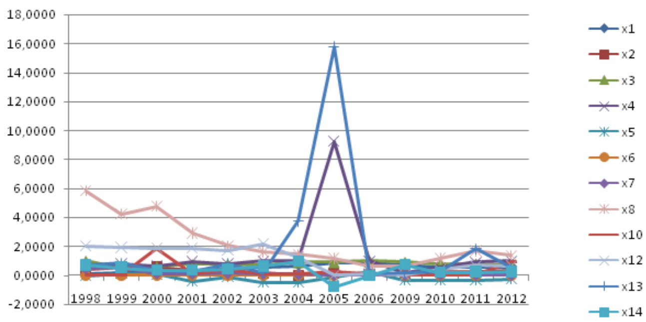
For C_{10}, although all ratios are split in the range zero and one, technical profit decreased in last years of the company. 2005 year is chosen to be used in the analysis. For C_{11}, since ratios related to liability increased and premium production ratio decreased in the last years of the company, 2002 year of data is chosen. For C_{12}, X_9 and X_{11} are not shown due to have extreme values. The company stopped premium production in years of 2007 and 2008. The most appropriate year to be employed in the analysis is chosen as 2003.



(a) C_{10}



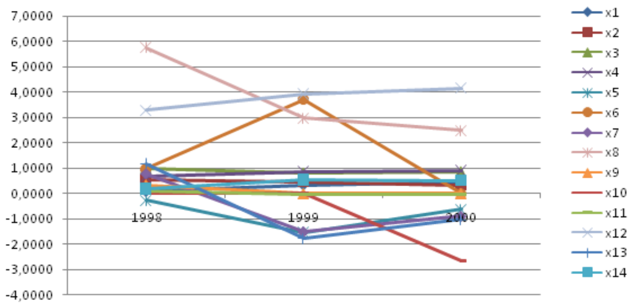
(b) C_{11}



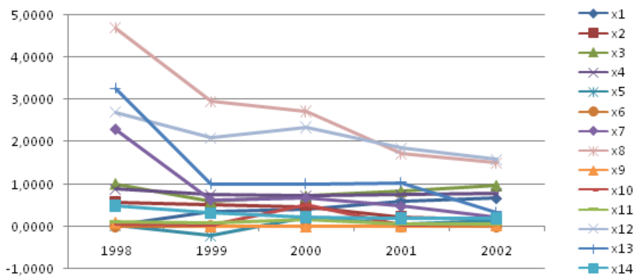
(c) C_{12}

Figure A.4: Financial indicators of the companies C_{10}-C_{12}

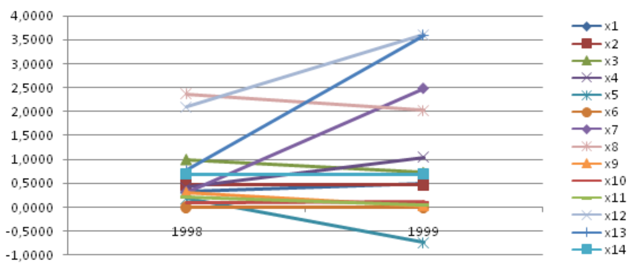
For C_{13}, some financial ratios of the company is close to one although it is expected to be close zero. At the same time, X_8 which is liability ratio is so high in the year of 2000. Therefore, that year is chosen. For C_{14}, while its ratios related to liability decreased in years of the company, its income is also decreased. Data of 2000 year of the company is chosen. For C_{15}, since available financial details of two years of the company existed in our analysis period, last active year is chosen(1999).



(a) C_{13}



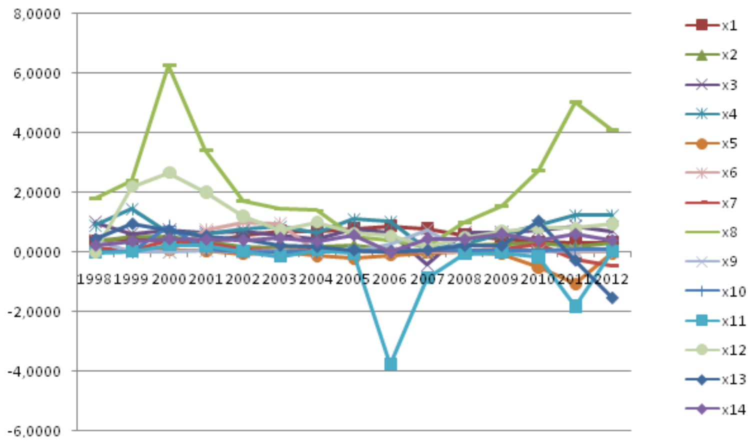
(b) C_{14}



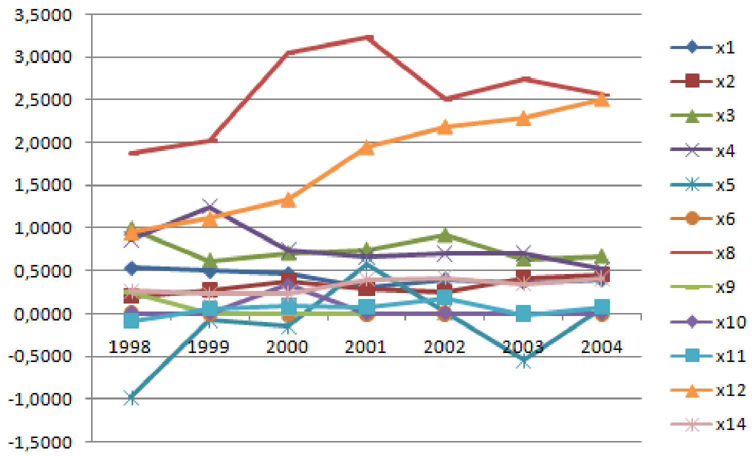
(c) C_{15}

Figure A.5: Financial indicators of the companies C_{13}-C_{15}

For C_{16}, in 2006, technical profit decreased to negative values. Therefore, 2006 is chosen. For C_{17}, X_7 and X_{13} ratios are excluded from the graphic because of having extreme values in 2001.



(a) C_{16}

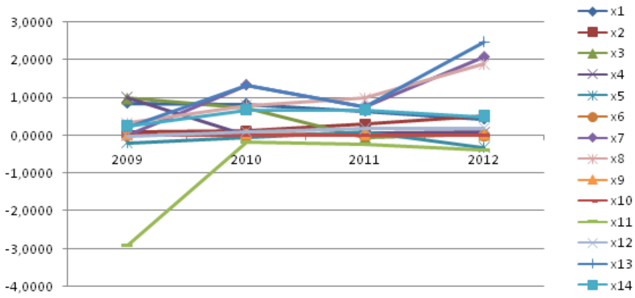


(b) C_{17}

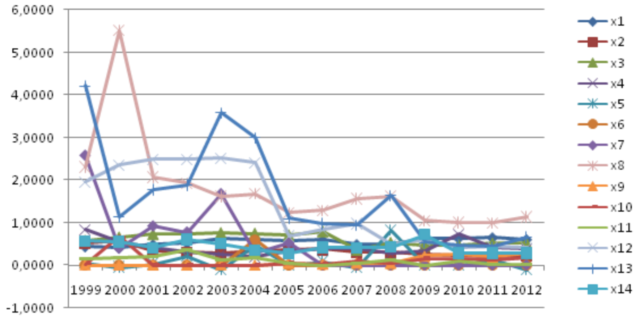
Figure A.6: Financial indicators of the companies C_{16}-C_7

Existing Companies

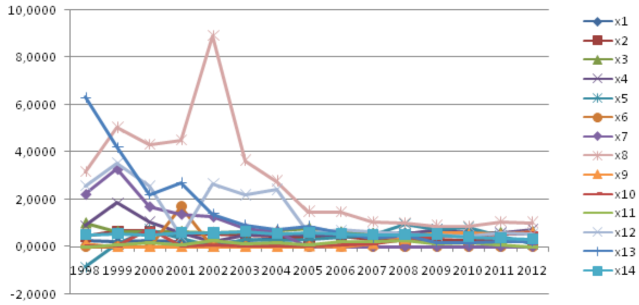
For C_{18}, the company started to act insurance with negative profit, however it improved itself by the years. 2010 year is chosen as best year to be used in the analysis. For C_{19}, since the company maintain its position during years, 2009 year is chosen the best year to be used in the analysis. For C_{20}, The company improved its position in last years and 2011 year of financial details are chosen in the analysis. For C_{21}, all ratios apart



(a) C_{18}



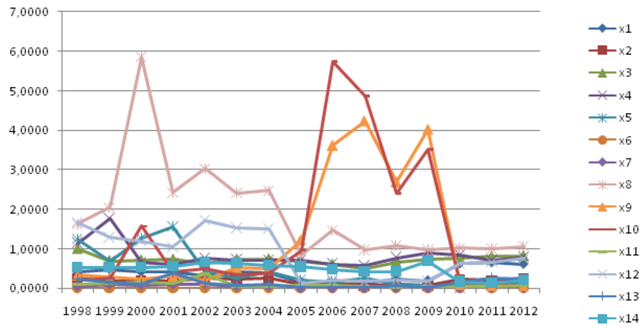
(b) C_{19}



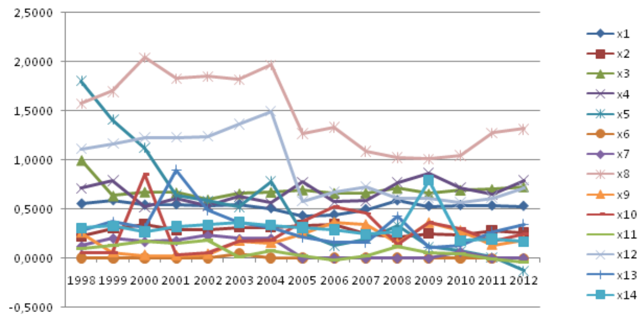
(c) C_{20}

Figure A.7: Financial indicators of the companies C_{18}-C_{20}

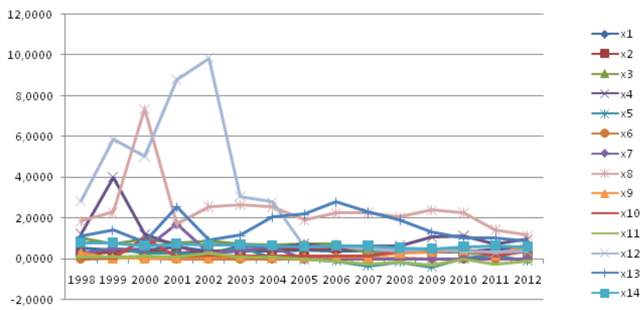
from X_9 and X_{10} are in the range of zero and one. 2011 year is chosen to be used in the analysis. For C_{22}, the company nearly keeps its financial stability in years and 2011 year of it is chosen. For C_{23}, apart from X_8, all ratios in during year of the company are in the range of zero and one and no extreme value was seen. 2011 year is chosen like all existing companies in the analysis.



(a) C_{21}



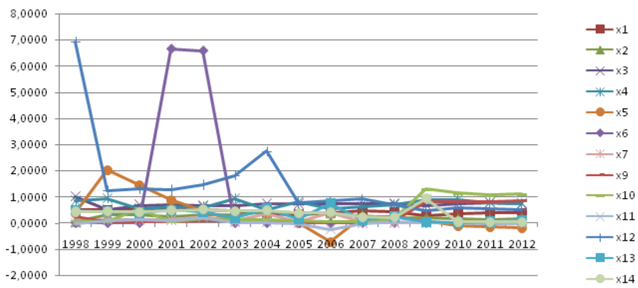
(b) C_{22}



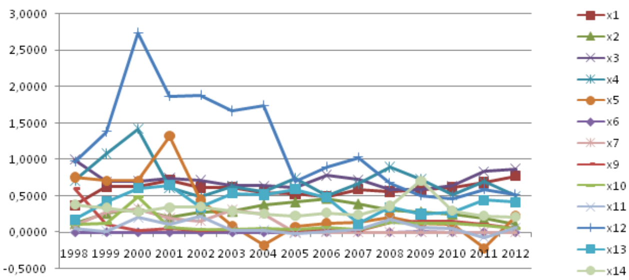
(c) C_{23}

Figure A.8: Financial indicators of the companies C_{21}-C_{23}

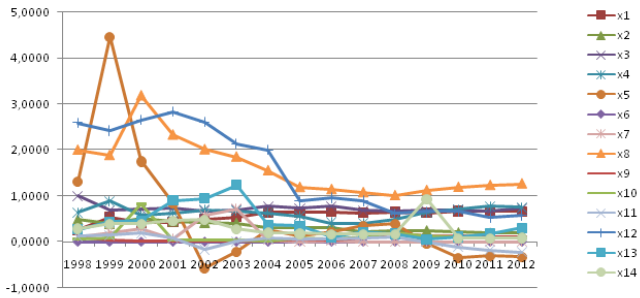
For C_{24}, X_8 ratio is excluded due to have extreme value in 2000. The name of the company was changed in 2006. 2008 year of financial details is chosen as best reflector as an acting company. For C_{25}, after changing its name in 2006, loss ratio of the company decreased and 2012 year is selected to be used in the analysis. For C_{26}, it is seen that the company kept its position in last years by looking its ratios since they are all in the range of zero and one. In 2008, its name was changed and it effected in a good way. Data of 2008 year of the company is chosen.



(a) C_{24}



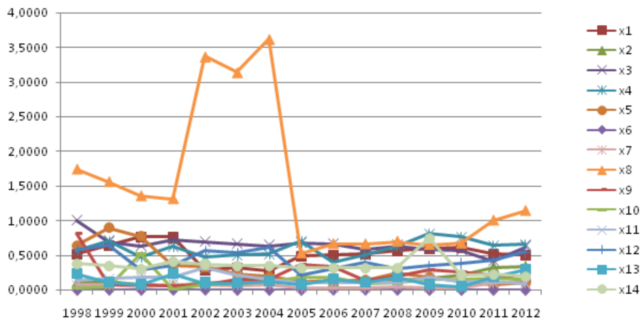
(b) C_{25}



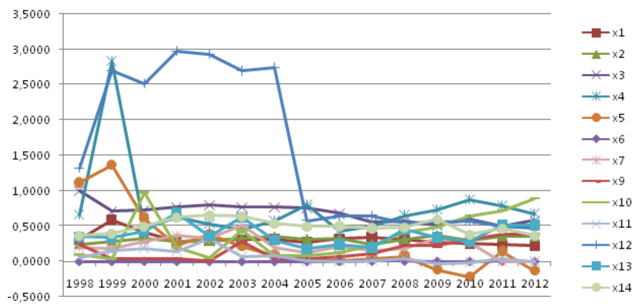
(c) C_{26}

Figure A.9: Financial indicators of the companies C_{24}-C_{26}

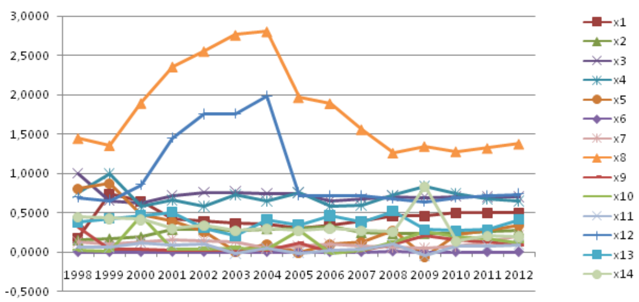
For C_{27}, except X_8, all ratios kept its position in during years. 2010 year is selected to be used in the analysis. For C_{28}, X_8 ratio had the value of eight in 2000, therefore that rate was not added to the graphic. The best applicable year is is chosen as 2007 for that company. For C_{29}, since all ratios are stayed constantly apart from X_8 and 2012 year is selected for the analysis.



(a) C_{27}



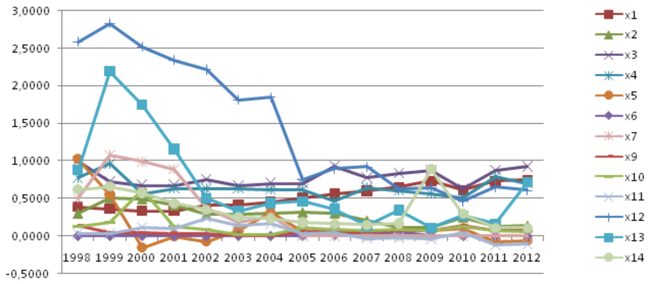
(b) C_{28}



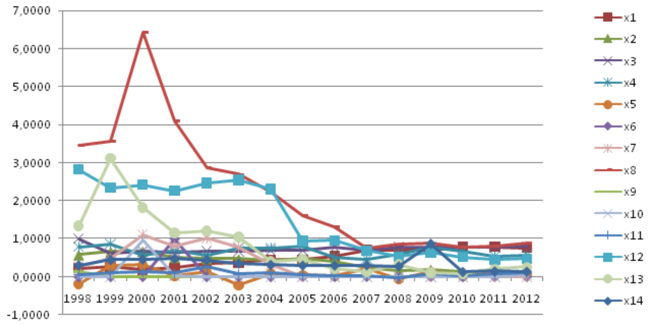
(c) C_{29}

Figure A.10: Financial indicators of the companies C_{27}-C_{29}

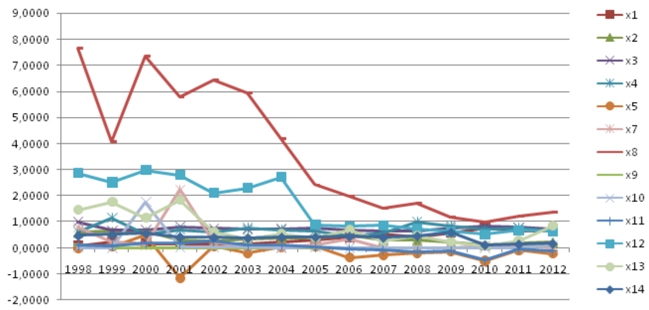
For C_{30}, X_8 is not included to the graphic since it had high value as a rate. 2010 year of the company is chosen as an applicable data. For C_{31}, the company is seen to keep its position during the years and 2012 year is selected to be used in the analysis. For C_{32}, X_6 is not included due to have high value in 2000. However, it decreased to normal level in five years. Financial details of 2011 year are employed in the analysis.



(a) C_{30}



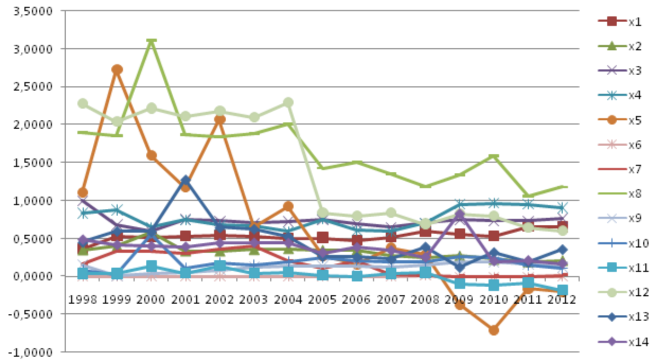
(b) C_{31}



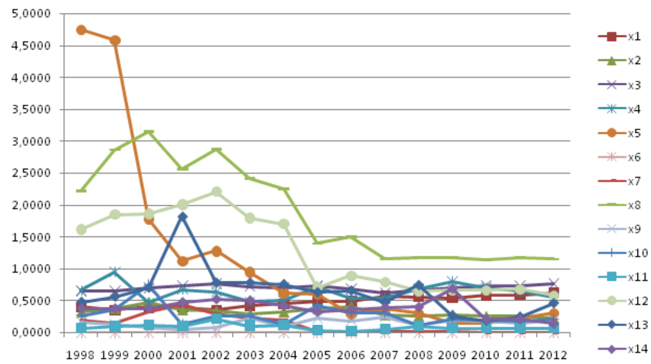
(c) C_{32}

Figure A.11: Financial indicators of the companies C_{30}-C_{32}

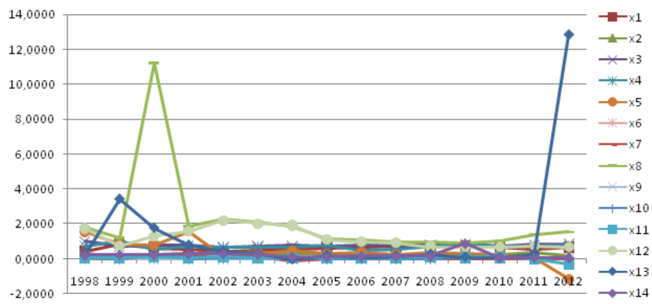
For C_{33}, the company changed its name in 2009 and it caused to have negative profit in the proceeding years. Therefore, 2007 year of the company is selected as the most applicable one as an active company. For C_{34}, although some ratios related to liability are high, other ones kept constantly in years. Therefore, 2012 year of data is used in the analysis. For C_{35}, as it is seen from the graphic, until 2012 the company kept its position during years even it had high liability ratio and negative profit in that year. Therefore, 2011 year is selected to be applied.



(a) C_{33}



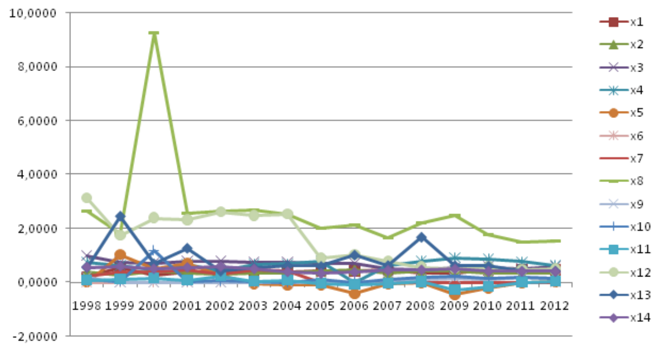
(b) C_{34}



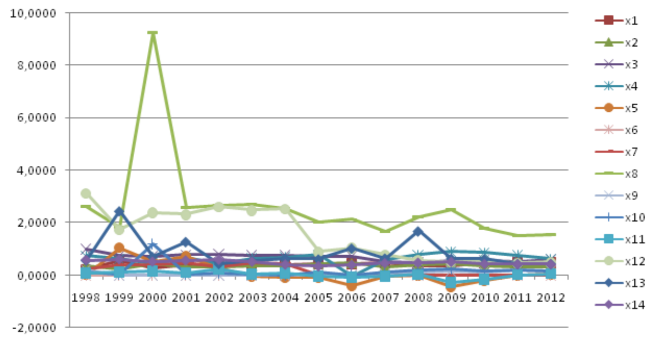
(c) C_{35}

Figure A.12: Financial indicators of the companies C_{33}-C_{35}

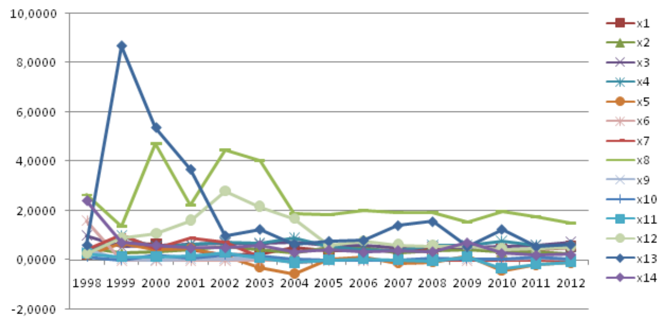
For C_{36}, from 2001, the company kept its financial position. 2012 year of data is used in the analysis. For C_{37}, apart the extreme values of the company regarding liability in 2000, it is seen as a stable company. Therefore, last year, 2012, is used in the analysis. For C_{38}, like all companies, the firm had an extreme values related to liability in 2000. 2012 financial data of the company is selected for the analysis.



(a) C_{37}



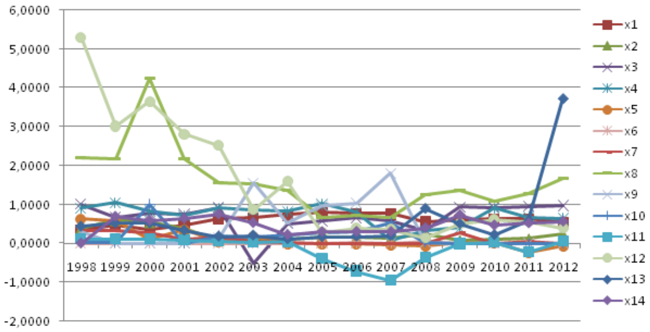
(b) C_{37}



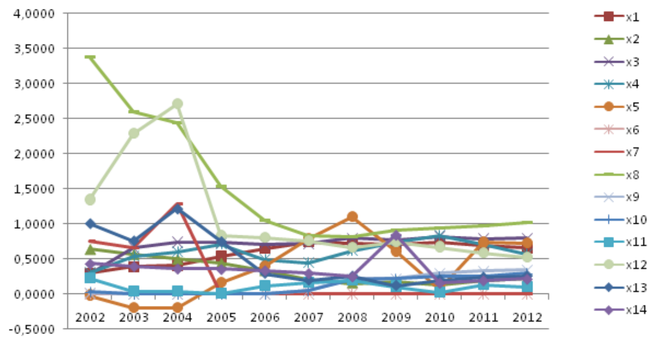
(c) C_{38}

Figure A.13: Financial indicators of the companies C_{36}-C_{38}

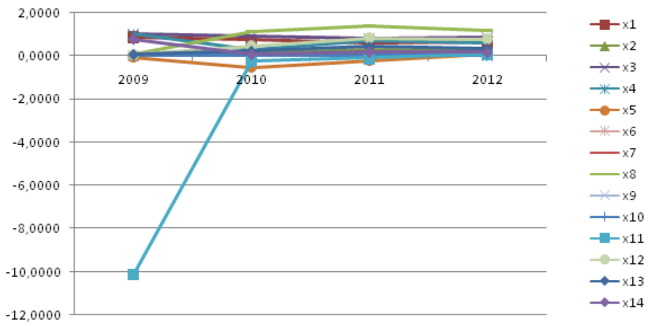
For C_{39}, since the ratio related to reinsurance shares increased in last years of the company, 2009 year of data is used in the analysis. For C_{40}, the company has maintained his position during the years. Therefore, 2012 was used in the analysis. For C_{41}, when the company first entered to the market, it had a negative profit. But then that value was jumped to positive and 2012 year of data data is selected for the analysis.



(a) C_{39}



(b) C_{40}



(c) C_{41}

Figure A.14: Financial indicators of the companies C_{33}-C_{35}

APPENDIX B

SPSS OUTPUTS OF THE LOGISTIC MODELS

Table B.1: Beginnig classification table of logistic regression considering only constant

Number of Steps	Variable Name		Predicted Group Membership		Total
			.00	1.00	
Step 0	Dependent Variable	.00	24	0	100.0
		1.00	17	0	0.0
Overall Percantage					58.5
a. Constant is included in the model.					
b. 100% of cross-validated grouped cases correctly classified.					

Table B.2: Classification table of logistic regression including 14 financial ratios

Number of Steps	Variable Name		Predicted Group Membership		Total
			.00	1.00	
Step 1	Dependent Variable	.00	24	0	100.0
		1.00	5	12	0.0
Overall Percantage					87.6
Step 2	Dependent Variable	.00	24	0	100.0
		1.00	1	16	97.6
Overall Percentage					97.6
b. The cut value is .500					

Table B.3: Result of significance of the logistic regression

Hosmer and Lemeshow Test			
Step	Chi-square	df	Sig.
1	19.824	8	.011
2	7.820	8	.451
3	.000	7	1.000

Table B.4: Classification of the logistic regression with additional variables

Classification Table					
Observed			Predicted		
			Dependent Variable		Percentage Correct
			.00	1.00	
Step 1	Dependent Variable	.00	22	2	91,7
		1.00	1	16	94.1
	Overall Percentage				92.7
Step 2	Dependent Variable	.00	23	1	95,8
		1.00	1	16	94.1
	Overall Percentage				95.1
Step 3	Dependent Variable	.00	24	0	100.0
		1.00	0	17	100.0
	Overall Percentage				100.0
a The cut value is .500					

Table B.5: Significance test of the logistic regression with additional variables

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	28.081	1	.000
	Block	28.081	1	.000
	Model	28.081	1	.000
Step 2	Step	18.121	1	.000
	Block	46.202	2	.000
	Model	46.202	2	.000
Step 3	Step	9.435	1	.002
	Block	55.637	3	.000
	Model	55.637	3	.000

Table B.6: Explanation power of the logistic regression with additional variables

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	27.556	.496	.668
2	9.435	.676	.910
3	.000	.743	1.000
a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.			
b. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.			
c. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.			

Table B.7: Coefficients of variables in the logistic model applied to the data including additional variables

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1	Duration	-.521	.142	13.366	1	.000	.594
	Constant	5.227	1.600	10.680	1	.001	186.320
Step 2	Loss Ratio	17.403	9.332	3.477	1	.062	36127677.826
	Duration	-.939	.400	5.513	1	.019	.391
	Constant	-1.251	3.115	.161	1	.688	.286
Step 3	Loss Ratio	303.753	28305.758	.000	1	.991	8.286E+131
	Profit/Paid Capital	-18.174	2365.438	.000	1	.994	.000
	Duration	-12.584	1158.562	.000	1	.991	.000
	Constant	-61.762	7259.194	.000	1	.993	.000
a Variable(s) entered on step 1: Duration							
b Variable(s) entered on step 2: Loss Ratio							
c Variable(s) entered on step 3: Profit/Paid Capital							

APPENDIX C

BAYESIAN REGRESSION CODES AND PREDICTION OF COMPANIES

Coding of Bayesian Regression in Matlab [29]

```
veri = xlsread('cox.xlsx');
y = veri(:,1);
x = veri(:,2:8);
n = 41; k=7;
r = [1.035 0.231 -0.098 0.130 0.066 -0.137 -0.057 ]'; % prior means
R = eye(k); T = diag([0.00638 0.00082 0.00108 0.00122 0.00087 0.00099 0.00005]');
% prior variance
Q = chol(inv(T)); q = Q*r;
b0 = (x'*x) (x'*y); % use ols as initial values
sige = (y-x*b0)'*(y-x*b0)/(n-k);
xpx = x'*x; xpy = x'*y; % calculate x'x, x'y only once
qpq = Q'*Q; qpv = Q'*q; % calculate Q'Q, Q'q only once
ndraw = 10000; nomit = 100; % set the number of draws
bsave = zeros(ndraw,k); % allocate storage for results
ssave = zeros(ndraw,1);
tic;
for i=1:ndraw; % Start the sampling
xpxi = inv(xpx + sige*qpq);
b = xpxi*(xpy + sige*qpv); % update b
b = norm_rnd(sige*xpxi) + b; % draw MV normal with mean(b), var(b)
bsave(i,:) = b'; % save b draws
e = y - x*b; ssr = e'*e; % update sige
chi = chis_rnd(1,n); % do chisquared(n) draw
sige = ssr/chi;
ssave(i,1) = sige; % save sige draws
end; % End the sampling
toc;
bhat = mean(bsave(nomit+1:ndraw,:)); % calculate means and std deviations
bstd = std(bsave(nomit+1:ndraw,:)); tstat = bhat./bstd;
sighat = mean(ssave(nomit+1:ndraw,1));
tout = tdi_sprb(tstat',n); % compute t-stat significance levels % set up for printing
results
```

```
in.cnames = strvcat('Coefficient','t-statistic','t-probability');
in.rnames = strvcat('Variable','intercept','X4','X5','X8','X10','X13','Duration');
in.fmt = '%16.6f';
tmp = [bhat' tstat' tout];
fprintf(1,'Gibbs estimates /n'; % print results
mprint(tmp,in);
result = theil(y,x,r,R,T); % compare to Theil-Goldberger estimates
prt(result); Predicted Classification of the firms
```

Table C.1: Prediction of the bayesian model for acting companies in 2013

	Box-Cox Bayesian							
	2006	2007	2008	2009	2010	2011	0.2274 2012	2013
C_{16}					0.5545	0.2269	0.2511	0.3441
C_{17}	0.4861	0.1607	0.4056	-0.2380	0.0749	0.3493	0.0200	-0.0077
C_{19}	0.5080	0,8454	0,8471	0,9323	0,7961	0,3992	0,2129	0,1996
C_{20}	0.4489	0.4457	0.5379	0.4234	0.4087	0.3428	0.2354	0.3825
C_{42}	0.8451	0.5677	0.8608	0.7481	0.4403	0.6873	0.7927	0.2562
C_{24}	0.4201	0.1948	0.2420	0.2592	0.3870	0.4437	0.3329	0.4036
C_{33}	0.3407	0.2112	0.4026	0.3668	0.3052	0.2493	0.2744	0.6298
C_{22}	0.6834	0.8109	0.6783	0.6154	0.7365	0.8823	0.6770	0.6770
C_{1}	0.8725	1.2590						
C_{23}	0.5312	0.3765	0.6689	0.6130	0.2780	0.1262	0.2093	-0.0464
C_{3}	0.8867	1.0644		0.4477	0.1000	0.1668	-0.1418	0.4386
C_{38}	0.6817	0.3908	0.2810	0.3247	0.3819	0.6214	0.4422	0.1999
C_{18}	0.3239	0.1789	0.1890	0.0675	0.0911	0.0143	0.2318	0.1908
C_{21}	0.5963	0.2974	0.6261	0.3273	0.4385	0.9461	0.1153	0.1970
C_{26}	0.6787	0.3992	0.6609	0.6940	0.7025	1.0377	0.6891	0.6801
C_{5}	0.9182	0.5281	0.7576	0.7064	0.7365	0.8823	0.6770	0.6836
C_{28}	0.5419	0.3263	0.6857	0.4031	0.2757	0.2588	0.3036	0.2474
C_{29}	0.5700	0.3779	0.2810	0.3381	0.2909	0.1774	0.0484	0.0566
C30	0.6910	0.5278	0.7634	0.8786	0.4150	0.4162	0.2610	0.2842
C31	0.4456	0.4637	0.5146	0.4307	0.6572	0.8706	0.4384	0.4214
C32	0.2551	0.2903	0.3669	0.3069	0.3174	0.2993	0.2140	0.0895
C7	0.4035	0.7638						
C8	0.5370	0.8592						
C40					0.5364	0.7249	0.8521	0.1130
C34	0.7265	0.7068	0.6785	0.5014	0.6725	0.6166	0.3240	0.0833
C9	0.9338	1.0998						
C35	0.6104	0.8341	1.7978	1.1674	0.7054	0.5214	0.4559	
C36	0.5550	0.3395	0.3772	0.3225	0.1692	0.6003	0.2370	0.1248
C15	0.5803	0.7840	-0.1690	0.1193	0.3868	0.8981	1.4052	1.0726
C37	0.5042	0.6052	-0.0739	0.0694	0.1167	0.4141	0.1506	-0.0075
C11	1.1243	0.6889			0.1362	0.2784	0.1399	0.6645
C25	0.3467	0.1013	0.3382	0.2961	0.2741	0.2393	0.1970	0.1581
C27	0.7165	0.5001	0.6304	0.4321	0.4338	0.3359	0.2430	0.1412
C41						0.2418	0.3589	0.0915

Table C.2: Prediction of the bayesian model with indicators for acting companies in 2013

Box-Cox Bayesian								
	2006	2007	2008	2009	2010	2011	2012	2013
C16					W	S	S	S
C17	S	S	S	S	S	S	S	S
C19	S	I	I	I	W	S	S	S
C20	S	S	W	S	S	S	S	W
C42	I	W	I	S	S	W	W	S
C24	S	S	S	S	S	S	S	S
C33	S	S	S	S	S	S	S	W
C22	W	I	W	W	W	I	W	W
C1	I	I						
C23	S	S	W	W	S	S	S	S
C3	I	I		I	S	S	S	W
C38	W	S	S	S	S	W	W	S
C18	S	S	S	S	S	S	S	S
C21	S	S	W	S	S	I	S	S
C26	I	S	W	W	W	I	W	W
C5	I	S	W	W	W	I	W	I
C28	S	S	W	S	S	S	S	S
C29	S	S	S	S	S	S	S	S
C30	I	I	W	I	S	S	S	S
C31	S	S	S	S	W	I	W	W
C32	S	S	S	S	S	S	S	S
C7	S	W						
C8	S	I						
C40					W	I	I	S
C34	W	W	W	W	W	W	S	S
C9	I	I						
C35	W	I	I	I	W	W	W	S
C36	S	S	S	S	S	W	S	S
C15	S	W	S	S	S	I	I	I
C37	S	W	S	S	S	S	S	S
C11	I	W			S	S	S	W
C25	S	S	S	S	S	S	S	S
C27	W	S	W	S	S	S	S	S
C41						S	S	S