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PREDICTING ROMANIAN FINANCIAL DISTRESSED COMPANIES

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1. ABSTRACT

The study consisted in collecting financial information for a group of distressed and non-distressed Romanian listed companies during the period 2006–2008, in order to create early warning signals for financial distressed companies using the following methodologies: the Logistic and the Hazard model, the CHAID decision tree model and the Artificial Neural Network model (ANN). For each company a set of 14 financial ratios, that reflect the company's profitability, solvency, asset utilization, growth ability and size, were calculated and then used in the study. A Principal Component Analysis was also used to reduce the dimensionality of the data space and to allow seeing that the 2 types of companies do form 2 distinct groups suggesting that the ratios used are useful enough to predict financial distress.

The following 4 data sets were separately analyzed: first-year data to predict distress one year ahead, second-year data for a 2 year-ahead prediction, third-year data for a 3 year-ahead prediction, as well as cumulative three-year data to predict distress 1 year ahead by letting the ratios vary in time. For each data set, several prediction models were created using CHAID, the Logit and Hazard models as well as the ANN and the hybrid-ANN. The results are consistent with the theory and also to previous studies and the out-of-sample forecast accuracy of the estimated models of 73%-100% indicates that the proposed early warning models for the Romanian listed companies are quite efficient.

2. INTRODUCTION

The current financial crisis has already thrown many companies out of business all over the world. All this happened because they were not able to face the challenges and the unexpected changes in the economy. In Romania, for example, a study made by Coface Romania and based on the data provided by the National Trade Register Office, stated that around 14.483 companies became financially distressed by the end of the year 2008, when they had difficulties paying off their financial obligations to its creditors due to inadequate cash flows. Moreover, the chances of financial distress or even bankruptcy increased when a firm had high fixed costs, illiquid assets, or revenues that are sensitive to economic downturns.

Looking at the above situation, we realize how important it is to understand the reasons behind the collapse of a company. Knowing these reasons might hinder a company from being financially distressed and early actions could be taken as a precaution. Predicting corporate financial distress accurately and efficiently is therefore very important for any bank, investor, company and regulatory authority. Keeping far away from bankruptcy is the base for each enterprise to survive and develop. Only when a company can build up an efficient early warning system for financial distress and take effective actions before happening, will the company manage to keep on-going in the fierce competition.

Taking this into account, the purpose of this paper consists in collecting financial information for a group of distressed and non-distressed Romanian listed companies during the period 2006–2008, for which data were available, in order to create early warning signals for financial distressed companies using several types of models and methodologies, that were chosen according to the results obtained from other similar studies. Since the distress prediction issue was intensively studied for several decades, quite a lot of methodologies were found to have accurate forecasting results. From them all: **the Logistic** and **the Hazard model, the CHAID decision tree model** and **the Artificial Neural Network model** were found to be most efficient and were therefore chosen for this prediction study of the Romanian financial distressed companies.

For each company a set of 14 financial ratios were calculated and then used in the process of identifying and predicting the distressed companies. The study also includes **a Principal Component Analysis**, that reduces the dimensionality of the initial financial data space in order to allow visual description of the total sample of distressed and non-distressed companies and to check if the financial ratios used in the study can be useful enough to predict financial distress. For each prediction model, several forecasting performances were tested, by considering the following 4 individual data sets: first-year data for a 1 year-ahead prediction, second-year data for a 2 year-ahead prediction, third-year data for a 3 year-ahead prediction, as well as cumulative three-year data to predict distress 1 year ahead by letting the ratios vary in time. The main purpose of the study consists in identifying early warning models that best perform in- and out-of-sample, together with the best financial predictors.

3. LITERATURE REVIEW

Prediction of corporate financial distress and bankruptcy is a subject which has gained a great deal of interest by researchers in finance starting in the late 1960s. The first step in the evolution of the quantitative firm failure prediction model was taken by **Beaver** (1966), who developed a dichotomous classification test based on a simple *t*-test in a univariate framework. He used individual financial ratios from 79 failed and non-failed companies that were matched by industry and assets size in 1954 to 1964 and identified a single financial ratio – *Cash flow/ Total Debt* as the best predictor of corporate bankruptcy.

Beaver's study was then followed by **Altman** (1968), who suggested a multivariate technique, known as Multivariate Discriminant Analysis (**MDA**). By using 33 bankrupt companies and 33 non-bankrupt companies over the period 1946 – 1964, five variables were selected to be most relevant in predicting bankruptcy. These five were: *Working Capital to Total Assets*, *Retained Earnings to Total Assets, Earnings before Interest and Taxes to Total Assets, Market Value of Equity to Book Value of Total Debt* and *Sales to Total Assets*.

Z-Score was determined and those companies with a score greater than 2.99 fell into the non-bankrupt group, while those companies having a Z-Score below 1.81 were in the bankrupt group. The area between 1.81 and 2.99 is defined as the zone of ignorance or the gray area. The MDA model was able to provide a high predictive accuracy of 95% one year prior to failure. For this reason, MDA model had been used extensively by researchers in bankruptcy research (Altman, Haldeman and Narayanan (1977); Apetiti (1984); Shirata (1998)).

However, Eisenbeis (1977), Ohlson (1980) and Jones (1987) found that there were some inadequacies in MDA with respect to the assumptions of normality and group dispersion. The assumptions were often violated in MDA and this may biased the test of significance and estimated error rates.

Logit analysis which did not have the same assumptions as MDA was made popular in the financial distress prediction problem by **Ohlson** (1980). He used 105 bankrupt companies and 2058 non-bankrupt companies from 1970 to 1976. The results showed that *size,* financial structure (*Total Liabilities to Total Assets*), performance and current liquidity were important determinants of bankruptcy. In the logistic analysis, average data is normally used and it is considered as a single period model. Hence, for each non-distressed and distressed company, there is only one company-year observation. The dependent variable is categorized into one of two categories that is distressed or non-distressed.

In 1984, **Zmijewski's** (1984) **probit model** was first applied to the firm failure prediction. However, this type of binary econometric model was less intensely used in this field. Some studies that implied the use of logistic and probit models for the distress prediction problem were made by Lennox (1999) and Menard (1995).

In 2004, some econometric problems with the single period logit model were discussed by Hillegeist (2004). First, is the sample selection bias that arises from using only one, non-randomly selected observation for each bankrupt company, and second, the model fails to include time varying changes to reflect the underlying risk of bankruptcy. Being based on a dichotomous classification, the traditional static model is not suited to handle the temporal concept. The dichotomous approach treats all firms that belong to each group the same and there will be no recognition of default timing, whether it falls within the window or not. The failure process must be fairly stable over a considerable period of time for this specification to work properly.

Shumway (2001) demonstrated that these problems could result in biased, inefficient, and inconsistent coefficient estimates. To overcome these econometric problems he proposed **the hazard model** for predicting bankruptcy and found that it was superior to the logit and the MDA models. This particular model is actually a multi-period logit model because the likelihood functions of the two models are identical. For this reason, the discrete-time hazard model with time-varying covariates can be estimated by using the existing computer packages for the analysis of binary dependent variables. The main particularities of the hazard model consist in the facts that firm specific covariates must be allowed to vary with time for the estimator to be more efficient and a baseline hazard function is also required, but which can be estimated directly with macroeconomic variables to reflect the radical changes in the environment.

Further on, **Nam, Kim, Park and Lee** (2008) extended the work of Shumway (2001) and developed a duration model with time varying covariates and a baseline hazard function incorporating macroeconomic variables, such as exchange rate volatility and interest rate. Using the proposed model, they investigated how the hazard rates of listed companies in the Korea Stock Exchange (KSE) are affected by changes in the macroeconomic environment and by time varying covariate vectors that show unique financial characteristics of each company. By investigating the out-of-sample forecasting performances of their model compared to the results of both a traditional dichotomous static model and also a logit model with time-varying covariates but no baseline hazard function, they demonstrated the improvements produced when allowing temporal and macroeconomic dependencies.

In another study, **Abdullah, Halim, Ahmad** and **Rus** (2008) compared three methodologies of identifying financially distressed companies in Malaysia, that are: multiple discriminant analysis (MDA), logistic regression and hazard model. In a sample of 52 distressed and non-distressed companies with a holdout sample of 20 companies, the predictions of hazard model were accurate in 94,9% of the cases examined. This was a higher accuracy rate than generated by the other two methodologies.

However, when the holdout sample was included in the sample analyzed, MDA had the highest accuracy rate of 85%. Among the ten determinants of corporate performance examined, the Ratio of *Debt to Total Assets* was a significant predictor of corporate distress regardless of the methodology used. In addition, *Net Income Growth* was another significant predictor in MDA, whereas the *Return on Assets* was an important predictor when the logistic regression and hazard model methodologies were used. Their analysis was similar to the studies of Low, Fauzias and Ariffin (2001), Mohamed and Sanda (2001), Zulkarnain, Mohamad Ali, Annuar and Abidin (2001).

In recent years many types of heuristic algorithms such as **neural networks** and decision trees have also been applied to the bankruptcy prediction problem and several improvements in the financial distress prediction were noticed. For example the studies made by **Tam and Kiang** (1992), **Salchenberger et al.** (1992) and **Jain B. A. and B. N. Nag** (1998) provided evidence to suggest that neural networks outperform conventional statistical models such as discriminant analysis, logit models in financial applications involving classification and prediction.

Soon after that, **hybrid Artificial Neural Network methods** were proposed in some financial distress prediction studies. For example, **Yim and Mitchell** (2005) tested the ability of a new technique, hybrid ANN's to predict corporate distress in Brazil. The models used in their study were compared with the traditional statistical techniques and conventional ANN models. The results indicated that the most relevant financial ratios for predicting Brazilian firm failure are *Return on Capital Employed, Return on Total Assets, Net Assets Turnover, Solvency* and *Gearing*.

The first ratio tells how much the firm is earning on shareholder investment, being a measure of overall efficiency and a reflection on financial as well as operational management. ROA measures the efficient utilization of the company's assets in generating profits. As expected, low profitability ratio is associated with high probability of failure. The solvency ratio is the total of shareholders' funds per total assets. Failed firms had a low solvency ratio because it implies that these firms are predominantly financed with debt. The lower the level of solvency is, the lower the chances of the firm to meet its obligations are. The asset management ratio is the net asset turnover. This measures the company's effectiveness in using its total assets and is calculated by dividing total assets into sales. This ratio shows how many dollars of sales have been generated for every one dollar of asset employed. Low activity ratio is associated with high probability of failure. Last, the gearing ratio is defined as the debt per equity and indicates how much of the company's financial structure is debt and how much is equity. A high ratio indicates greater leverage.

The results of the study also suggested that hybrid neural networks outperform all other models in predicting firms in financial distress one year prior to the event, concluding that hybrid ANN is a very useful tool in early warning systems for predicting firm failure.

The main disadvantage of neural network models, however, consists in the difficulty of building up a neural network model, the required time to accomplish iterative process and the difficulty of model interpretation. Compared to neural networks, decision tree is not only a non-linear architecture, which is able to discriminate patterns that are not linearly separable and allow data to follow any specific probability distribution, but also plain to interpret its results, require little preparation of the initial data and perform well with large data in a short time.

Zheng and Yanhui (2007) used **decision tree** methodologies for corporate financial distress prediction in their study. The authors presented the advantages of using CHAID decision trees in comparison to a neural network model, which is complicated to build up and to interpret or to a statistic model such as multivariate discriminate regression and logistic regression, where the patterns need to be linearly separable and samples are assumed to follow a multivariate normal distribution. Their study focused on 48 failed and continuing Chinese listed companies in the period 2003–2005. The following variables embodied most information for predicting financial distress: *Net Cash Flow from Operating Activity as a percentage of Current Liabilities, Return Rate on Total Assets, Growth rate of Total Assets* and *Rate on Accounts Receivable Turnover*.

They also noticed that it is not appropriate to use financial information to predict financial distress ahead of four years. However, the results supported by the test study showed that decision trees was a valid model to predict listed firms' financial distress in China, with a 80% probability of correct prediction.

Another similar study based on CHAID decision tree models for distress prediction problem was made by **Koyuncugil A. S.** and **N. Ozgulbas** (2007). They identified Return on Equity (ROE) to be the best financial early warning signal for detecting financial distress of the Small and Medium-sized Enterprises listed in Istanbul Stock Exchange for the period 2000-2005.

As noticing from the literature review presented above, the bankruptcy and distress prediction issues were intensively studied starting with the late 1960s and still remain an opened challenge, especially in the times when the financial crisis tests each company's surviving skills even more. In this context, early warning signals could be of great help in preventing financial distress or even bankruptcy.

4. RESEARCH DESIGN

4.1. Data description

For this study, public financial information for the period 2005–2008 was collected from the Bucharest Stock Exchange's web site. The sample consisted in 100 Romanian listed companies on RASDAQ, having similar characteristics, as being included in the same III–R market category. The choice for this sample out of a total of 1645 listed companies on RASDAQ was made with the purpose of having two equal groups of "distressed" and "non-distressed" companies, as most of the distress prediction studies had.

A financial distress company indicates the case when promises to creditors of a company are broken or honored with difficulty and may even lead to bankruptcy. Since there is no standard definition for classifying "distressed" and "non-distressed" companies, however, it is more difficult to decide on which grounds to classify the companies accordingly, than in the simpler case of a bankrupt or non-bankrupt company, in which the status of a company is quite obvious, but for which less financial data is available. Referring however to other similar studies on financial distressed companies (Zheng and Yanhui (2007), Psillaki, Tsolas and Margaritis (2008)) I followed the same main criteria for proper classification of the companies. That is why, a company was considered "distressed" in case it had losses and outstanding payments for at least two consecutive years.

Following this classification rule, there were only 55 Romanian distressed companies in the year 2008 on RASDAQ, out of which 5 did not have all the required information for all of the years 2005-2008. To summarize, in order to have two equal groups of distressed and non-distressed companies, for this study were chosen all the 50 distressed companies for which financial information was available and other 50 non-distressed similar companies by assets size and activity field, that were chosen randomly.

4.2. Financial ratios

As noted by **Scott (1981),** many of the variables that appeared in most empirical work do not rest on any strong underlying theory, but mostly on their popularity of usage in the literatures and on the predictive success stated in previous research. Thus, the selection of the main set of financial ratios for this study was based on the previous results presented in the related work, but also restricted to the financial data provided by the Bucharest Stock Exchange. That is why, there were 14 financial ratios calculated for the purpose of this study and grouped into 5 distinct categories, reflecting the company's profitability, solvency, asset utilization, growth ability and size. The main definition of each of the 14 financial ratios is presented in the table below.

Table 1. Financial Ratios

Category	Code	Financial ratios	Definition
Profitability	**I1**	Profit Margin	Net Profit or Loss / Turnover *100
	I2	Return on Assets	Net Profit or Loss / Total Assets *100
	I3	Return on Equity	Net Profit or Loss / Equity *100
	I4	Profit per employee	Net Profit or Loss / number of employees
	I5	Operating Revenue per employee	Ln(Operating revenue / number of employees)
Solvency	**I6**	Current ratio	Current assets / Current liabilities
	I7	Debts on Equity	Total Debts / Equity *100
	I8	Debts on Total Assets	Total Debts / Total Assets *100
Asset utilization	**I9**	Working capital per employee	Working capital / number of employees
	I10	Total Assets per employee	Ln(Total Assets / number employees)
Growth ability	**I11**	Growth rate on net profit	(Net P/ L_1 - Net P/L_0) / Net P/L_0
	I12	Growth rate on total assets	(Total $Assets_1$ – Total $Assets_0$) / Total $Assets_0$
	I13	Turnover growth	($Turnover_1$- $Turnover_0$) / $Turnover_0$
Size	**I14**	Company size	ln (Total Assets)

As noticing, some of the financial ratios were transformed by applying the natural logarithms, while others are expressed in percentages. The purpose was to bring all values to a similar scale. The only variables for which the log transformation was not possible because of the presence of some negative values were: I4 and I9.

Profitability ratio is represented by **Profit Margin (I1),** computed as Net Profit or Loss divided by Turnover, **Return on Assets (I2)**, calculated as a ratio between Net Profit and Total Assets, **Return on Equity (I3)** representing the ratio between Net profit and Equity, **Profit per employee (I4)** and **Operating Revenue per employee (I5)**. All these financial ratios are common measures of managerial performance and are therefore vital in the study of financial distress. Ohlson (1980), Lennox (1999) and Zulkarnain et al. (2001) showed that profitability is an important determinant of distress. It is expected that companies with large profits have a lower probability of distress. Hence the relationship between them is negative.

In addition to the above ratios, solvency is also an important element to be looked into as it measures the ability of a company to meet its financial obligations, thus avoiding corporate failures. Such financial ratios are **Current ratio (I6),** calculated as the ratio between Current

Assets and Current Liabilities, **Debts on Equity (I7),** which is computed as Total Debts divided by Equity and **Debts on Total Assets (I8).** The last one, **I8** explains the extent to which a company relies on debt financing rather than equity and provides information on a company's insolvency and its ability to secure additional financing for good investment opportunities. This is to ensure that creditors are protected.

Another aspect regarding a company's economic activity is described by the way assets are being utilized. This can be measured by financial ratios such as **Working capital per employee (I9)** and by **Total Assets per employee (I10)**.

Moreover, annual dynamic indicators of a company's changes in profit, Assets and Turnover (that are **I11, I12 and I13),** might provide relevant information of how efficient the activity of a company is. The rationale behind these ratios is that healthy company's net profit and sales grow rapidly as compared to distressed companies. Hence, it is expected that the greater the growth, the healthier is the company.

Another factor that seems to discriminate between distressed and non-distressed companies is size, which is measured by total assets employed **(I14)**. Big companies normally have large assets base if compared with smaller companies. Ohlson (1980) found that size was significant in discriminating between distressed and non-distressed companies. It is expected that the relationship between these two variables is negative, the larger the size of a company, the lower the probability of distress or even bankruptcy.

4.3. Models and methodologies

4.3.1. Principal Component Analysis

Principal component analysis (PCA) is a way of identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where graphical representation is not available, PCA is a powerful tool for analyzing data. The other main advantage of PCA is that once you have found these patterns in the data, you can compress the data by reducing the number of dimensions, without much loss of information. By dimensionality reduction in a data set, only those characteristics of the data set that contribute most to its variance are kept.

PCA involves a mathematical procedure that reduces the dimensionality of the initial data space by transforming a number of possibly correlated variables into a smaller number of uncorrelated variables called *principal components*. These components are synthetic variables of maximum variance, computed as a linear combination of the original variables. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. PCA involves the calculation of the eigenvalue decomposition of a data covariance matrix, usually after mean centering the data for each attribute.

Principal Component Analysis algorithm is given below:

STEP 1: Identifying missing values or "abnormal" values (extreme values which affect the average)

STEP 2: Centering and reducing the initial observations - necessary due to heterogeneity of measurement units

STEP 3: Calculating the correlation matrix of the initial variables

STEP 4: Calculating linear combinations of the initial variables (the eigenvectors) in order to maximize the variance and to generate uncorrelated principal components

STEP 5: Choosing the number of principal components based on Kaiser's criterion: ordering the eigenvectors in a descending eigenvalues order (largest first), and then retaining those components which have their eigenvalues greater than 1, meaning they bring more information than the original variables (centered and reduced);

STEP 6: Principal components interpretation

STEP 7: Plotting individuals on the retained principal components space

If the data is concentrated in a linear subspace, this provides a way to compress data without losing much information and simplifying the representation. By picking the eigenvectors having the largest eigenvalues we lose as little information as possible in the mean-square sense. PCA offers, therefore, a convenient way to control the trade-off between losing information and reducing the dimension of the initial representation of the data.

4.3.2. CHAID Decision Tree Model

A decision tree is a predictive model build in the process of learning from instances, which can be viewed as a tree. Specifically each branch of the tree is a classification question and the leaves of the tree are partitions of the dataset with their classification. Because of their tree structure and ability to easily generate consistent rules for segmentation of the original database, decision trees can become an efficient method to predict financial distress. There are a lot of useful decision tree algorithms, out of which the most common are: J. Ross Quinlan's decision tree algorithms called **ID3** and **C4.5,** Classification and Regression Trees of **CART** and Chi-square Automatic Interaction Detector (**CHAID**). While ID3, C4.5 and CART generate binary trees, CHAID, although similar to CART, has the advantage of generating non-binary trees.

CHAID decision tree model was originally designed to handle categorical attributes only. For each input attribute, CHAID finds the pair of values that is least significantly different with respect to the target attribute. The significant difference is measured by the *p*-value obtained from a statistical test. The statistical test used depends on the type of the target attribute. If the target attribute is continuous, an F-test is used, if it is categorical, then a Pearson chi-square test is used, if it is ordered, then a likelihood-ratio test is used. For each selected pair, CHAID checks if *p*-value obtained is greater than a certain merge threshold. If the answer is positive, it merges the values and searches for an additional potential.

CHAID algorithm is given below:

STEP 1: For each predictor variable X, find the pair of categories of X that is least significantly different (has the largest p value) with respect to the target binominal variable Y. The method used to calculate the p value for our study is **Pearson chi-squared test**.

STEP 2: For the pair of categories of X with the largest p value, compare the p value to a pre-specified alpha level α_{merge}

a. if the p value is greater than α_{merge}, merge this pair into single compound category. As a result, a new set of categories of X is formed, and the process starts over at step 1.
b. if the p value is less than α_{merge}, go to step 3.

STEP 3: Compute the adjusted p value for the set of categories of X and the categories of Y by using a proper Bonferroni adjustment.

STEP 4: Select the predictor variable X that has the smallest adjusted p value (the one that is most significant). Compare its p value to a pre-specified alpha level α_{split}

a. if the p value is less than or equal to α_{split}, split the node base on the set of categories of X.
b. if the p value is greater do not split node. The node is a terminal node.

STEP 5: Continue the tree-growing process until the stopping rules are met.

The advantage of a CHAID classification tree is that it generates consistent rules for classifying the initial database.

4.3.3. The Logistic Model

According to Shumway (2001), the **logistic model** is a single-period classification model which uses maximum likelihood estimation to provide the conditional probability of a firm belonging to a certain category given the values of the independent variables for that firm. It describes the relationship between a dichotomous variable Y, that takes values 1 or 0 for 'distress' and 'non-distress', respectively, and k explanatory variables $x_1, x_2, ..., x_k$, representing financial ratios. Since Y is a binary variable, it has a Bernoulli distribution with parameter p = P (Y = 1), that is, p is the probability of distress for given values x_1, x_2,., x_k of the explanatory variables and also the mean, since E[Y] = P (Y = 1) = p. The logistic regression model is defined as follows. Suppose that Y_1,..,Yn are independent Bernoulli variables and let p_i denote the mean value of Y_i, that is, p_i= E[Yi] =P(Yi =1). The mean value p_i can be expressed in terms of the explanatory variables $x_{i,1}$, $x_{i,2}$,..,$x_{i,k}$ as:

$$p_i = \frac{1}{1 + e^{-(\beta_0 + \sum_{j=1}^{k} \beta_j x_{i,j})}} \qquad (1)$$

When applying the logit-transformation to the above equation, we get a linear relationship between logit(p_i) and the explanatory variables:

$$\mathrm{logit}(p_i) = \log\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \sum_{j=1}^{k} \beta_i x_{i,j} \quad (2)$$

This equation is sometimes called the **logit form** of the model. Note that, logit(p_i) is the log odds (that is, the logarithm of the odds) of distress for the given values $x_{i,1}$, $x_{i,2}$,..,$x_{i,k}$ of the explanatory variables.

An important issue in using binary state prediction models such as logit analysis is the selection of the cutoff probability which determines the classification accuracy. In order to classify an observation into one of the two groups, the estimated probability from the logit model is compared to a pre-determined cutoff probability, which in the case of equal groups of distressed and non-distressed companies in the data set, the cutoff is set to 0.5. If the estimated probability is below the cutoff, the observation is classified as non-distressed and if the estimated probability is above the cutoff, it is considered distressed. However, there is no clear cut approach to determine the optimal cutoff probability since it depends on the decision context and payoff functions. Previous studies in the literature have used arbitrary cutoff probabilities, mostly 0.5, but some also tested the results over multiple cutoffs.

4.3.4. The Hazard Model

In his bankruptcy prediction studies, Shumway (2001) described a **hazard model** as a multi-period logit model, which includes a *time dependent baseline hazard function*. He also defined a multi-period logit model as a logit model that is estimated with data on each firm in each year of its existence as if each firm-year were an independent observation and showed that a multi-period logit model is equivalent to a discrete-time hazard model because the likelihood functions of the two models are identical. The main characteristics of the hazard model are time varying covariates and the presence of a baseline hazard function.

There are actually various ways in which a baseline hazard function can be specified. For instance, if the baseline hazard rate is assumed to be a constant term, then the model becomes duration-independent. In Shumway (2001), for example, a time-invariant constant term, ln(age), was used and the individual hazard rate for firm *i* was then independent of a particular point of time.

However, there are also examples of using a duration-dependent form of the baseline hazard rate. For instance in Beck et al. (1998) the baseline hazard term was a dummy variable marking the length of the sequence of zeros that precede the current observation. Notice that the baseline hazard rate using such a type of time dummies implies that an individual hazard rate is determined by each firm's survival period. Indirect measures like time dummies, however, can be less effective in capturing economy wide effects since the firm's historical survival period cannot properly reflect the overall macro-dependencies and their correlations. Since the recent economic crises, the study of the macroeconomic factors has become a major concern, which generated a new approach of the baseline hazard functions by incorporating macroeconomic variables. Hillegeist et al. (2001) handled temporal dependencies by using two direct measures of the baseline hazard rate: the rate of recent defaults (RRD) and changes in interest rates (CIR). Later on, Nam, Kim, Park and Lee (2008) also examined the volatility of foreign exchange rate (VFE) and found that it serves better as a direct measure for the baseline hazard rate in bankruptcy prediction of a sample of 367 listed companies in the Korean Stock Exchange for the period 1991 - 2000.

The hazard model is therefore a duration model with time varying covariates, which is not only effective but also more flexible since the influence of the macroeconomic environment can be easily formulated by altering the shape of the baseline hazard function.

The hazard function, h(t), can be measured as the conditional probability of bankruptcy or distress at time t, given survival to that time.

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \le T \le t + \Delta t \ \left| T \ge t \right.)}{\Delta t} = \frac{f(t)}{S(t)} \quad (3)$$

where T represents the time of failure of a company and is a continuous random variable that follows a probability density function f(t) and a cumulative density function F(t). S(t) is the survival function, which represents the probability that a firm survives over the time t.

$$S(t) = P(T \ge t) = 1 - F(t) = \int_t^{\infty} f(u)du \qquad (4)$$

Hence, the hazard function can be interpreted as the instantaneous risk of a bankruptcy or distress. The most widely used hazard model is the following: Cox's (1972) semiparametric proportional hazard model.

$$h(t|x_i) = e^{x_i \beta} \cdot h(t|0) \qquad (5)$$

where x_i represents covariates composed of financial statement items of each company i =1...N. The first part of the equation represents a firm-specific part which is considered time invariant, while the second expression is the baseline hazard function, which is time-dependent. A more flexible form of a hazard model with time varying covariates can be written as:

$$h(t|x_{i,t}) = e^{x_{i,t}\beta} \cdot h(t|0) \quad (6)$$

where $h(t|x_{i,t})$ represents the individual hazard rate of company *i* at time *t* and $x_{i,t}$'s are covariate vectors composed of financial statements of each company *i* at time *t*. Shumway (2001) pointed out that if we model multiple-period data in a static model then we would be ignoring the fact that firms' financial conditions change through time and the estimates will be biased and inconsistent. Using all the stacked data instead of a single period observation will enhance the efficiency of the estimates and the out-of-sample forecasting performance will be improved.

The hazard model, given by equation (6), can be estimated through the following form of a multi-period logit model:

$$P(y_{i,t} = 1|x_{i,t}) = h(t|x_{i,t}) = \frac{e^{\alpha(t) + \beta x_{i,t}}}{1 + e^{\alpha(t) + \beta x_{i,t}}} \quad (7)$$

where $h(t|x_{i,t})$ is the hazard function, $x_{i,t}$ represents the vector of explanatory variables used to forecast distress, $\alpha(t)$ is a time varying covariates and β is the coefficient vector. This final form of a hazard function will be used in the present study both in the case were the baseline hazard function is time-invariant and also when it is time varying and described through macroeconomic variables.

4.3.5. The Artificial Neural Network Model

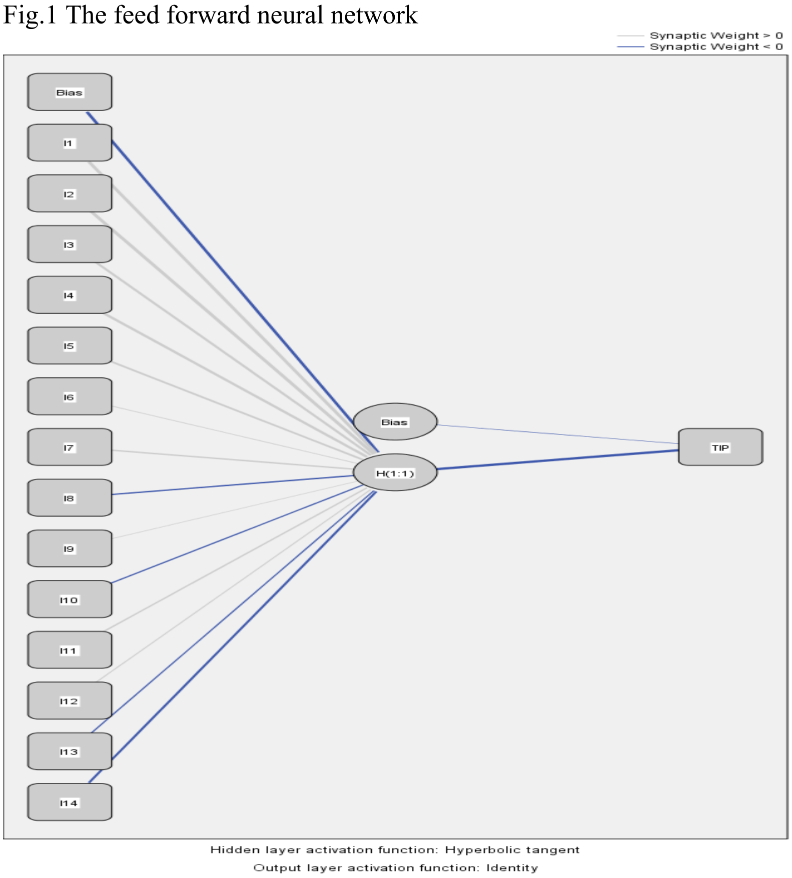
Neural network models appear to be a promising alternative to statistical techniques in the distress prediction problem. Unlike parametric statistical models, they do not need to specify the functional relationship between variables. They are adaptive and respond to structural changes in the data generating process in ways that parametric models cannot. The purpose of the model is to capture the causal relationships between dependent and independent variables in the data set under consideration. Neural networks have the ability to construct nonlinear models by scanning the data for patterns. Existing literature suggests that the neural network techniques are capable of representing models of any functional form.

The basic components of a neural network consist of several neurons which represent processing elements. Each of these processing elements receives input values which are added and converted to an output value by a transfer function. When the output value exceeds a threshold level, the neuron is activated and the output is fed to the next layer. The neurons are organized hierarchically into layers, with the first layer referred to as the input layer, the last layer as the output layer, and the intermediate layers as the hidden layers. The connections between different layers are in the form of weights which are a measure of the connection strength between two neurons which are in two succeeding layers. The weights can also be interpreted as the contribution rate of the output of the neuron in the current layer to the neuron in the succeeding layer. The weights are generated by an iterative training process by presenting examples to the network.

For this study, the design of the neural network was based not only on the availability of data inputs but also on the desired classification output. First, among the numerous neural network algorithms available, the supervised *feedforward backpropagation* algorithm, which minimizes the errors, was selected as being the most appropriate for the task. Then, one hidden unit layer was selected, after following Jain and Nag's study (2004), while the number of nodes to be used in the hidden layer was set to one, in order to avoid overfitting. The number of nodes in the input layer was already determined by the number of input variables (14 representing the financial ratios used in the study), while the output was a prediction from a single node, generating values between 0 and 1 with which the companies were classified between distressed and non-distressed.

The multilayer structure of the feed forward neural network used in this study is therefore the following: an input layer, one hidden layer and one output layer. Every neuron x on a layer L is connected to all the neurons y on the next layer L+1. A (directed) connection between two neurons x and y has a weight w(x,y) and every neuron has an activation function (*tansig* for the hidden layer and *logsig* for the output layer). The network starts with arbitrary weights and modifies them during the training stage, in order to minimize the error function (the difference between the output of the network and the desired output). A non-linear supervised learning method like the *gradient descent* technique is used to adjust the weights. The training stage lasted for 2000 iterations or until the error was below a specified threshold (10^{-15}). The network was trained in order to learn how to classify companies as distressed and non-distressed. The described network is presented in fig. 1.

Fig.1 The feed forward neural network



5. RESULTS OF THE ANALYSIS

Several distress prediction models and methodologies were used in search for the model that has best out-of-sample accuracy and identifies the financial ratios that are most relevant in distress prediction problem. The study was structured in 5 main parts, accordingly to the main types of methods and methodologies used. Each part treats separately the following data sets:

- **first-year data,** when using just the financial ratios of the year 2008 to predict financial distress one year ahead
- **second-year data,** when using just the financial ratios of the year 2007 to predict financial distress two years ahead

- **third-year data,** when using just the financial ratios of the year 2006 to predict financial distress three years ahead
- **cumulative three-year data,** when using all the financial ratios of the years 2006 -2008 to predict financial distress one year ahead by letting the variables vary in time.

For each of the four data sets, a descriptive analysis was first conducted in order to be proper informed of any missing data, of the nature of the correlation between all 14 variables, of the differences in mean for each of the two types of companies, and of any other characteristics that can become helpful in the prediction study.

5.1. Descriptive statistics

First, the mean values of each of the 14 financial ratios for both types of distressed and non-distressed companies were calculated and presented in the following tables.

Table 2. Panel 1: Means for Non-distressed and distressed companies

PANEL 1: first- year data set		Non-distress		Distress	
		Mean	Std.dev.	Mean	Std.dev.
I1	Profit Margin	6,9	9,8	-53,6	70,1
I2	ROA	5,0	6,3	-14,5	16,0
I3	ROE	7,8	8,7	-12,7	66,0
I4	Profit per employee	9576,3	14967,4	-17340,0	15424,2
I5	Operating Revenue per employee	11,7	0,8	10,9	1,0
I6	Current ratio	3,8	5,2	3,2	6,2
I7	Total Debts on Equity	78,6	97,2	32,6	158,0
I8	Total Debts on Total Assets	32,0	23,8	54,3	50,8
I9	Working capital per employee	70581,0	273456,0	19653,0	232176,0
I10	Total Assets per employee	11,9	1,3	12,0	1,4
I11	Growth rate on net profit	63,7	127,9	34,4	108,8
I12	Growth rate on total assets	37,7	123,4	22,8	57,0
I13	Turnover growth	18,1	35,3	0,7	45,7
I14	Company size	16,6	1,5	16,5	1,6

Table 3. Panel 2: Means for Non-distressed and distressed companies

PANEL 2: second- year data set		Non-distress		Distress	
		Mean	Std.dev.	Mean	Std.dev.
I1	Profit Margin	7,568	11,31	-46,92	54,71
I2	ROA	5,77	7,44	-12,184	9,26
I3	ROE	8,9	10,93	-22,446	61,53
I4	Profit per employee	7614,698	10344,56	-18228,5	25236,80
I5	Operating Revenue per employee	11,55	0,79	10,72	0,81
I6	Current ratio	2,902	3,39	3,018	5,31
I7	Total Debts on Equity	76,754	92,01	65,44	173,48
I8	Total Debts on Total Assets	32,364	22,16	48,236	42,48
I9	Working capital per employee	75238,252	363987,06	29102,58	221324,39
I10	Total Assets per employee	11,63	1,16	11,63	1,21
I11	Growth rate on net profit	32,894	126,57	-16,604	136,83
I12	Growth rate on total assets	24,012	40,71	39,038	111,81
I13	Turnover growth	28,598	66,22	12,712	71,91
I14	Company size	16,426	1,43	16,412	1,66

Table 4. Panel 3: Means for Non-distressed and distressed companies

PANEL 3: third-year data set		Non-distress		Distress	
		Mean	Std.dev.	Mean	Std.dev.
I1	Profit Margin	8,698	22,47	-32,426	70,78
I2	ROA	6,424	14,96	-7,718	12,99
I3	ROE	10,478	22,58	-0,528	48,54
I4	Profit per employee	7142,524	13012,02	-6347,69	13719,67
I5	Operating Revenue per employee	11,338	0,78	10,528	0,86
I6	Current ratio	2,38	2,30	2,224	3,69
I7	Total Debts on Equity	80,062	92,79	62,922	155,09
I8	Total Debts on Total Assets	34,49	21,51	49,16	44,59
I9	Working capital per employee	34626,61	104414,90	-5729,48	36880,94
I10	Total Assets per employee	11,418	0,98	11,242	1,10
I11	Growth rate on net profit	94,616	443,34	-41,94	112,64
I12	Growth rate on total assets	18,39	34,26	37,768	173,97
I13	Turnover growth	15,28	35,82	-10,506	29,79
I14	Company size	16,248	1,42	16,294	1,49

Table 5. Panel 4: Means for Non-distressed and distressed companies

PANEL 4: cumulative three-year data set		Non-distress		Distress	
		Mean	Std.dev.	Mean	Std.dev.
I1	Profit Margin	5,3	18,7	-55,3	69,4
I2	ROA	4,1	10,8	-13,8	13,0
I3	ROE	6,6	25,2	-14,1	62,3
I4	Profit per employee	6302,0	12984,3	-17570,0	20068,6
I5	Operating Revenue per employee	11,4	0,9	10,7	0,9
I6	Current ratio	3,0	3,8	2,7	5,4
I7	Total Debts on Equity	78,1	106,7	46,8	164,1
I8	Total Debts on Total Assets	34,9	26,5	52,6	47,4
I9	Working capital per employee	50780	243521,1	15770,0	210550,3
I10	Total Assets per employee	11,1	1,1	11,8	1,3
I11	Growth rate on net profit	24,0	264,5	34,0	100,4
I12	Growth rate on total assets	26,9	82,2	34,9	129,1
I13	Turnover growth	16,9	48,2	1,3	54,2
I14	Company size	16,4	1,4	16,5	1,7

We first notice that the means of Profit Margin, ROA, ROE, Profit per employee and Operating Revenue per employee of distress companies have negative values for all data sets considered and are, therefore, as expected, lower than those of the non-distressed companies. Moreover, it appears that distressed companies rely more on debts, by approximately 54,3% in comparison to the healthy companies of only 32% when considering panel 1 with first-year data set, respectively by 48% for distressed companies when using second-year data set, 49% when including the third-year data set or by 52,6% in comparison to only 35% when using the panel with cumulated three-year data set.

Further on, net profit growth for distressed companies is around 34% for panels 1 and 4 and around 38 – 39 % for panels 2 and 3, whereas healthy companies net profit growth is 95% for panel 3 and 63.7% for the 2008 data set, but just 33% for panel 2 and 24% for the last panel. Similar to this case is the assets growth, while the turnover growth is extremely small for distressed companies in comparison to the healthy ones.

The mean values of the company size are quite close between the distressed and the non-distressed companies, for all panels, showing that both distressed and non-distressed companies of the initial sample were chosen wisely based on similarities grounds.

The following tables show the univariate analysis in order to identify ratios that have the highest ability to differentiate between financially distressed and non-distressed companies for each of the four panels. The results show that variables with a mean difference that is significant at the 5 % level for panels 1, 2 and 4 are: Profit Margin **(I1)**, ROA **(I2),** ROE **(I3),** Profit per employee **(I4),** Operating Revenue per employee **(I5),** Total debts on Total Assets **(I8)** and Turnover growth **(I13)** only for panel 1 and 4**.** Total Debts on Equity **(I7)** can also be included in the extended list for panels 1 and 4, based however, on an 8% significance level for panel 1, respectively 7% for panel 4.

Table 6. Panel 1: Mean differences for Non-distressed and distressed companies

PANEL 1: first-year data set		Mean		Mean differences	
		Non-distress	Distress	t-statistic	sig.
I1	Profit Margin	6,8	-53,6	-6,05	0,00
I2	ROA	5,0	-14,5	-8,01	0,00
I3	ROE	7,8	-12,7	-2,18	0,03
I4	Profit per employee	9576,3	-17340,0	-8,86	0,00
I5	Operating Revenue per employee	11,7	10,9	-4,58	0,00
I6	Current ratio	3,8	3,2	-0,51	0,61
I7	Total Debts on Equity	78,6	32,6	-1,75	0,08
I8	Total Debts on Total Assets	32,0	54,3	2,81	0,01
I9	Working capital per employee	70581,0	19653,0	-1,00	0,32
I10	Total Assets per employee	11,9	12,0	0,55	0,59
I11	Growth rate on net profit	63,7	34,4	-1,23	0,22
I12	Growth rate on total assets	37,7	22,8	-0,78	0,44
I13	Turnover growth	18,1	0,7	-2,12	0,04
I14	Company size	16,6	16,5	-0,26	0,79

Table 7. Panel 2: Mean differences for Non-distressed and distressed companies

PANEL 2: second- year data set		Mean		Mean differences	
		Non-distress	Distress	t-statistic	sig.
I1	Profit Margin	7,568	-46,92	-6,90	0,00
I2	ROA	5,77	-12,184	-10,69	0,00
I3	ROE	8,9	-22,446	-3,55	0,00
I4	Profit per employee	7614,698	-18228,5	-6,70	0,00
I5	Operating Revenue per employee	11,55	10,72	-5,18	0,00
I6	Current ratio	2,902	3,018	0,13	0,90
I7	Total Debts on Equity	76,754	65,44	-0,41	0,68
I8	Total Debts on Total Assets	32,364	48,236	2,34	0,02
I9	Working capital per employee	75238,252	29102,58	-0,77	0,45
I10	Total Assets per employee	11,63	11,63	0,00	1,00
I11	Growth rate on net profit	32,894	-16,604	-1,88	0,06
I12	Growth rate on total assets	24,012	39,038	0,89	0,38
I13	Turnover growth	28,598	12,712	-1,15	**0,25**
I14	Company size	16,426	16,412	-0,05	0,96

However, when considering, panel 3, which includes third-year data set, there are several changes in the mean difference significance. Although ROE (I3) is no longer significant, there are two new significant mean differences at a 5% significance. Those two are: **I9** and **I11.**

Table 8. Panel 3: Mean differences for Non-distressed and distressed companies

PANEL 3: third-year data set		Mean		Mean differences	
		Non-distress	Distress	t-statistic	sig.
I1	Profit Margin	8,698	-32,426	-3,92	0,00
I2	ROA	6,424	-7,718	-5,05	0,00
I3	ROE	10,478	-0,528	-1,45	**0,15**
I4	Profit per employee	7142,524	-6347,69	-5,04	0,00
I5	Operating Revenue per employee	11,338	10,528	-4,93	0,00
I6	Current ratio	2,38	2,224	-0,25	0,80
I7	Total Debts on Equity	80,062	62,922	-0,67	0,50
I8	Total Debts on Total Assets	34,49	49,16	2,10	0,04
I9	Working capital per employee	34626,61	-5729,48	-2,58	**0,01**
I10	Total Assets per employee	11,418	11,242	-0,84	0,40
I11	Growth rate on net profit	94,616	-41,94	-2,11	**0,04**
I12	Growth rate on total assets	18,39	37,768	0,77	0,44
I13	Turnover growth	15,28	-10,506	-3,91	0,00
I14	Company size	16,248	16,294	0,16	0,87

Table 9. Panel 4: Mean differences for Non-distressed and distressed companies

PANEL 4: cumulative three-year data set		Mean		Mean differences	
		Non-distress	Distress	t-statistic	sig.
I1	Profit Margin	5,3	-55,3	-9,20	0,00
I2	ROA	4,1	-13,8	-12,33	0,00
I3	ROE	6,6	-14,1	-3,41	0,00
I4	Profit per employee	6302,0	-17570,0	-11,40	0,00
I5	Operating Revenue per employee	11,4	10,7	-6,61	0,00
I6	Current ratio	3,0	2,7	-0,55	0,57
I7	Total Debts on Equity	78,1	46,8	-1,83	0,07
I8	Total Debts on Total Assets	34,9	52,6	3,68	0,00
I9	Working capital per employee	50780,0	15770,0	1,32	0,19
I10	Total Assets per employee	11,1	11,8	1,48	0,14
I11	Growth rate on net profit	24,0	34,0	0,47	0,64
I12	Growth rate on total assets	26,9	34,9	0,59	0,56
I13	Turnover growth	16,9	1,3	-2,53	0,01
I14	Company size	16,4	16,5	0,95	0,35

To conclude, here are the significant mean differences for each of the 4 sets of data:

- **first-year data set: I1, I2, I3, I4, I5, I8, I13 and I7**
- **second-year data set: I1, I2, I3, I4, I5 and I8**
- **third-year data set: I1, I2, I4, I5, I8, I9 and I11**
- **cumulative three-year data set: I1, I2, I3, I4, I5, I8, I13 and I7**

Next step consisted in calculating the correlation matrixes for the 4 sets of data in order to check the presence of any high correlation between the 14 financial ratios.

When using first-year data set, the correlation matrix presented in table 1 in ANNEXES indicates that the initial variables are not powerfully correlated. Medium correlations do exist, however, mostly between **I1 and I2** (57,2%), **I1 and I4 (**58,7%) **I1 and I5 (**56,5%), **I2 and I4** (52,8**%), I3 and I7** (-55,4%) and **I6 and I9** (50,4%).

The second correlation matrix presented in table 2 in ANNEXES also indicates the absence of any high correlations between variables, when considering second-year data set. Medium correlations exist, however, mostly between **I1 and I2** (60%), **I1 and I4 (**65%) **I1 and I5 (**53%), **I2 and I4** (63**%), I3 and I7** (-49%), **I5 and I10** (54%), **I5 and I4** (49%), **I6 and I9** (59%) and **I9 and I10** (53%).

In case of the third-year data set, there are two high correlations between variables **I4 and I1** (73%) and **I4 and I2** (75%), which indicates that in a PCA analysis, **I4** will have to be excluded from the analysis. There are also some medium correlations between: **I1 and I2** (60%), **I1 and I4 (**65%) **I1 and I5 (**53%), **I2 and I4** (63**%), I3 and I7** (-49%), **I5 and I10** (54%), **I5 and I4** (49%), **I6 and I9** (59%) and **I9 and I10** (53%). The correlation matrix is presented in table 3 in ANNEXES.

The last correlation matrix of the cumulative three-year data set presented in table 4 in ANNEXES indicates the absence of any high correlations between variables. Medium correlations do exist, however, mostly between **I1 and I2** (57%), **I1 and I4 (**63%) **I1 and I5 (**52%), **I2 and I4** (61**%), I3 and I7** (-46%), **I5 and I10** (48%), **I5 and I4** (48%), **I6 and I9** (52%) and **I9 and I10** (45%).

5.2. Principal Component Analysis

This principal component analysis was made for the total sample of 100 Romanian listed companies, by using each of the 4 data sets: first-year data set, second-year data set, third-year data set and cumulative three-year data set. The purpose of this section is to reduce the initial information space to a bi or 3- dimensional one, without losing much information and then see which of the financial ratios best describe the retained principal components. Several conclusions will be taken with the purpose of classifying the "healthy" and "unhealthy" Romanian listed companies, with the use of the retained principal components.

SPSS 16.0 software was used for this type of analysis. The set of data consisted in the financial ratios for the total sample of 100 Romanian listed companies, out of which 50 are "healthy" and 50 "unhealthy" and for each of the 4 data sets.

PANEL 1: first-year data set

Although there were no missing or abnormal values, the descriptive statistics of the 14 financial ratios indicated that the data had to be standardized before applying PCA. Moreover, since the correlation matrix indicated the absence of any strong correlations between the independent variables, there was no need to exclude any factor from the analysis. That is why, when first applying the PCA to the initial set of variables, according to the Kaiser criterion, which selects only eigenvalues greater than 1, 6 principal components resulted. They account for approximately 77% of the variability of the original space, which means that the PCA technique enabled the transformation of a 14-dimensional space into a 6-dimensional space losing only 23% of the information contained in the original space. The results are presented in table 5 in ANNEXES.

It is worth mentioning, however, that these first results of PCA do not provide useful information for identifying the reduced data space in which the companies can easily be identified as "healthy" or "unhealthy". To use PCA for this precise purpose, a selection of variables that are truly valuable in identifying distressed companies should first be made. PCA will then reduce the dimension of the selected variables space and will provide important information on the nature of the predictors.

That is why the new starting point for the PCA will be to decide upon which of the 14 variables can really provide significant information for both types of distressed and non-distressed companies and should, therefore, be included in the PCA. One way to decide upon them is to look back at the already identified ratios that have the highest ability to differentiate between financially distressed and non-distressed companies due to their mean differences. One other way will be to calculate the correlation coefficients between each of the 14 variables and the binary dependent variable that takes 1 if the company is distressed and 0 otherwise. The correlations between the binary variable and the 14 factors are given below.

Table 10.

Variable	Correlation coef.	Variable	Correlation coef.
I4	**-.667**	**I7**	**-.174**
I2	**-.629**	I11	-.124
I1	**-.521**	I9	-.101
I5	**-.420**	I12	-.078
I8	**.273**	I10	.055
I3	**-.215**	I6	-.051
I13	**-.209**	I14	-.026

The results are similar to the mean difference tests. The most correlated financial ratios to the binary dependent variable are the following: **I4** (Profit per employee), **I2** (ROA), **I1** (Profit Margin), **I5** (Operating Revenue per employee), **I8** (Total Debts on Total Assets) **I3** (ROE), **I13** (Turnover growth) and **I7** (Total Debts on Equity).

As a conclusion, the following financial ratios were also selected for a second PCA: **I1, I2, I3, I4, I5, I7, I8** and **I13**. The new eigenvalues are presented in the following table:

Table 11. **Total Variance Explained**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.944	36.806	36.806	2.944	36.806	36.806	2.380	29.747	29.747
2	1.665	20.807	57.613	1.665	20.807	57.613	1.767	22.088	51.835
3	1.138	14.223	71.835	1.138	14.223	71.835	1.600	20.000	**71.835**
4	.745	9.311	81.146						
5	.547	6.840	87.986						
6	.450	5.631	93.617						
7	.356	4.449	98.066						
8	.155	1.934	100.000						

The results indicated that the correlation matrix has only 3 eigenvalues greater than 1, being presented in the table in a descending order: λ_1=2,94, λ_2=1,67, λ_3= 1,138. Just like the theory suggested, the first principal component has the highest contribution consisting in 30% of the total gain of recovered information, followed by a 22% contribution of the second component and ending with a 20% more of the third component, leading to a total of 72% of the variability of the initial space. This shows that there are only these 3 components that have a greater contribution than the initial variables included in the analysis. The number of principal components retained was actually chosen according to the Kaiser criterion that is based on the eigenvalues greater than 1.

As a result, 3 principal components were retained in this analysis, with a total loss of only 28% of the initial information. Having determined the number of principal component retained and after reducing the 8-dimenional original space into a 3-dimensional space, we should now be concerned with the interpretation of the principal components. One common problem in PCA is that unrotated factor matrix often provides inconclusive interpretations. In order to solve this problem, the rotated component matrix can be calculated, using the Varimax procedure, which can be found in table 12.

Table 12 **Rotated Component Matrix[a]**

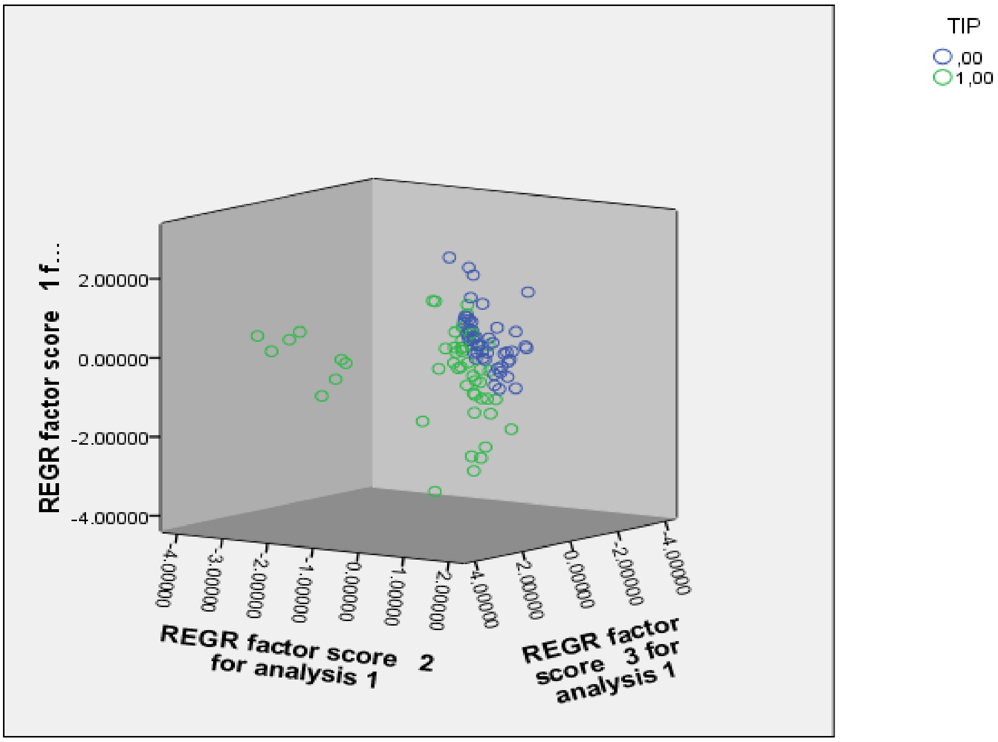
	Component		
	1	2	3
Zscore(I1)	.790	.309	.151
Zscore(I2)	.480	.741	-.002
Zscore(I3)	.253	.036	.872
Zscore(I4)	.504	.589	.129
Zscore(I5)	.816	.059	.041
Zscore(I7)	.212	.115	-.874
Zscore(I8)	.186	-.870	.157
Zscore(I13)	.679	-.022	-.101

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

The first principal component is powerfully correlated to I1 (Profit margin), I5 (Operating Revenue per employee) and I13 (Turnover growth) providing information on financial performance of a company. The second component is correlated with I2 (ROA), I4 (Profit per employee) and I8 (Total Debts on total Assets), while the third component is highly correlated to I3 (ROE) and I7 (Total Debts on Equity) and provides information regarding the proportion of Net Profit and Debts on Equity. We can say that first component represents the profitability and growth element, the second one is an Asset element, while the third principal component is a Debts and Equity element.

After plotting the total sample of 100 companies on a 3-dimensional graphic described by the 3 principal components retained from the PCA, where the distressed companies are green colored and the non-distressed companies are blue colored, it can be noticed that the two types of companies form 2 distinct groups, suggesting that the financial ratios used in this analysis are good enough to become predictors of financial distress.

Fig. 2. Distressed and non-distressed companies on a 3 principal component space



PANEL 2: second-year data set

After applying a similar PCA approach to the second data set, by analyzing the correlation matrix between variables and also the results form the mean difference tests between the distressed and non-distressed companies, it resulted the selection of the following factors to be included in the PCA: **I1, I2, I3, I4, I5, I8 and I7.**

The new eigenvalues are presented below:

Table 13. **Total Variance Explained**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.728	38.972	38.972	2.728	38.972	38.972	2.634	37.634	37.634
2	1.517	21.665	60.637	1.517	21.665	60.637	1.525	21.779	59.414
3	1.030	14.710	75.346	1.030	14.710	75.346	1.115	15.932	**75.346**
4	.722	10.311	85.658						
5	.526	7.516	93.173						
6	.264	3.765	96.938						
7	.214	3.062	100.000						

The results indicated that the correlation matrix has again only 3 eigenvalues greater than 1, being presented in table 13 in a descending order: λ_1=2,8, λ_2=1,5, λ_3= 1. The first principal component has the highest contribution consisting in 38% of the total gain of recovered information, followed by a 22% contribution of the second component and ending with a 16% more of the third component, leading to a total of **75%** of the variability of the initial space.

Table 14 **Rotated Component Matrix**[a]

	Component 1	2	3
Zscore(I1)	.873	.089	.090
Zscore(I2)	.821	.103	-.355
Zscore(I3)	.301	.823	-.013
Zscore(I4)	.779	.154	-.095
Zscore(I5)	.689	-.172	.159
Zscore(I7)	.162	-.878	.075
Zscore(I8)	-.014	-.056	.970

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

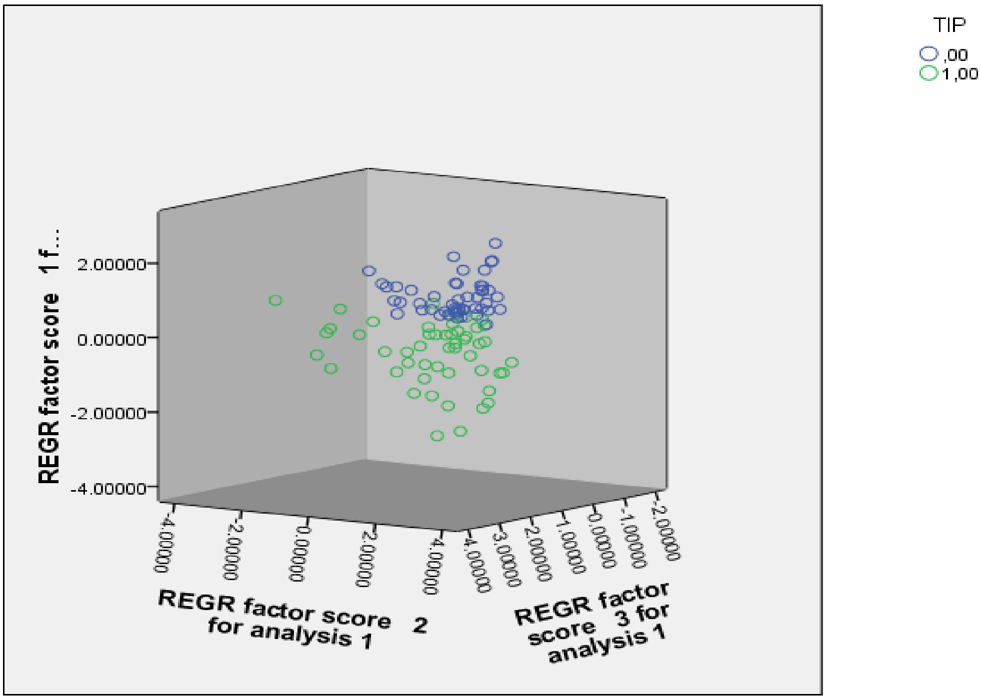
a. Rotation converged in 4 iterations.

The first principal component is powerfully correlated to I1 (Profit margin), I2 (ROA), I4 (Profit per employee) and to I5 (Operating Revenue per employee), the second component is highly correlated to I3 (ROE) and I7 (Total Debts on Equity) and provides information regarding the proportion of Net Profit and Debts on Equity, while the third component is only correlated with I8 (Total Debts on total Assets).

We can say that first component represents the profitability element, the second one is a Debts and Equity element, while the third principal component is an Asset element.

After plotting the total sample of 100 companies on a 3-dimensional graphic described by the 3 principal components retained from the PCA, where the distressed companies are green colored and the non-distressed companies are blue colored, we notice once again that the two types of companies form 2 distinct groups, suggesting that the financial ratios used in this analysis are good enough to become predictors of financial distress.

Fig. 3. Distressed and non-distressed companies on a 3 principal component space



PANEL 3: third-year data set

When using third-year data set, the following factors were considered relevant to be included in the PCA: **I1, I2, I5, I8, I9 and I11.** It is worth noticing that in this case, I4 was excluded from the analysis, because of high correlation to factor I1 and I2. The new eigenvalues are presented in the table 15:

Table 15. **Total Variance Explained**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.145	35.748	35.748	2.145	35.748	35.748	1.925	32.077	32.077
2	1.269	21.151	56.898	1.269	21.151	56.898	1.345	22.420	54.497
3	1.058	17.639	74.537	1.058	17.639	74.537	1.202	20.040	**74.537**
4	.810	13.496	88.033						
5	.371	6.189	94.222						
6	.347	5.778	100.000						

Extraction Method: Principal Component Analysis.

The results indicated that the correlation matrix has again only 3 eigenvalues greater than 1, being presented in the table in a descending order: λ_1=2,1 λ_2=1,3 λ_3= 1,1. The first principal component has the highest contribution consisting in 38% of the total gain of recovered information, followed by a 22% contribution of the second component and ending with a 16% more of the third component, leading to a total of **75%** of the variability of the initial space.

Table 16. **Rotated Component Matrix**[a]

	Component		
	1	2	3
Zscore(I1)	.902	-.060	-.041
Zscore(I2)	.737	.359	-.142
Zscore(I5)	.721	.037	.514
Zscore(I8)	.031	-.876	.202
Zscore(I9)	.211	.666	.323
Zscore(I11)	-.061	-.011	.878

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

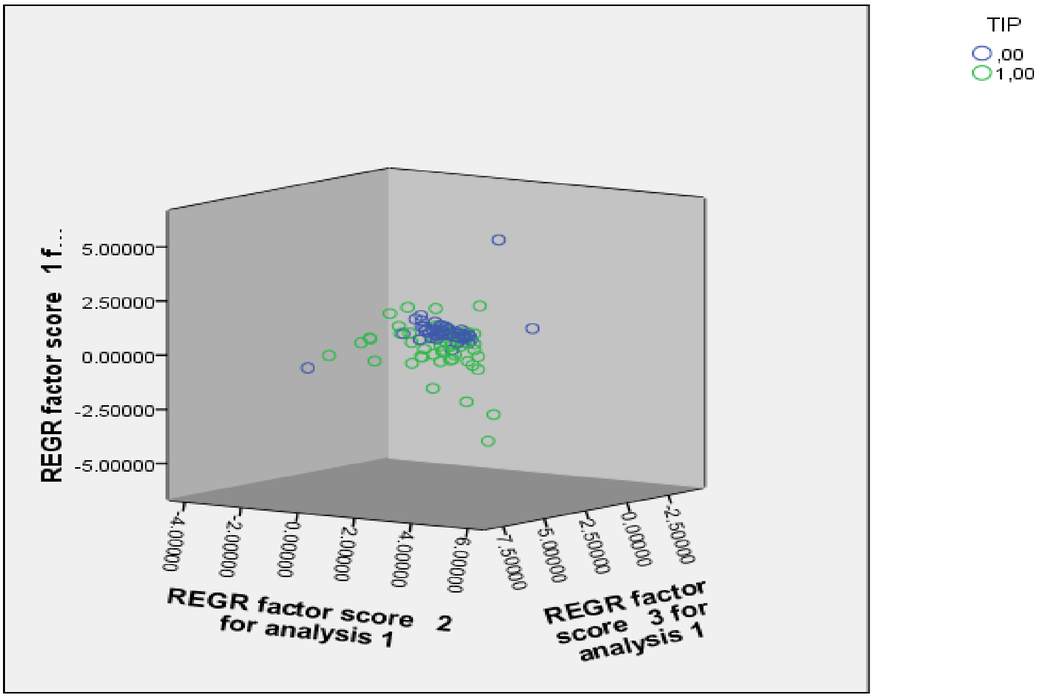
a. Rotation converged in 5 iterations.

The first principal component is powerfully correlated to I1 (Profit margin), I2 (ROA) and I5 (Operating Revenue per employee), the second component is highly correlated to I8 (Total Debts on total Assets) and I9 (Working capital per employee), while the third component is only correlated with I11 (Growth rate on net profit).

We can say that first component represents the profitability element, the second one is a Debts and Assets element, while the third principal component is a Profit Growth element.

When plotting the total sample of 100 companies on a 3-dimensional graphic described by the 3 principal components retained from the PCA, where the distressed companies are green colored and the non-distressed companies are blue colored, the results are, with minor exceptions, similar to the previous analysis.

Fig. 4. Distressed and non-distressed companies on a 3 principal component space



PANEL 4: cumulative three-year data set

After applying a similar approach, by analyzing the correlation matrix between variables and also the results form the mean difference tests between the distressed and non-distressed companies, it resulted the selection of the following factors to be included in the PCA: **I1, I2, I3, I4, I5, I8, I13 and I7.** It is worth noting that in this case, **I13** was also excluded from the analysis, since too little information could be saved during PCA. The new eigenvalues are presented in the table 17:

Table 17. **Total Variance Explained**

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.726	38.944	38.944	2.726	38.944	38.944	2.652	37.885	37.885
2	1.449	20.694	59.639	1.449	20.694	59.639	1.464	20.914	58.800
3	1.158	16.547	76.185	1.158	16.547	76.185	1.217	17.386	**76.185**
4	.627	8.962	85.148						
5	.525	7.496	92.644						
6	.323	4.620	97.264						
7	.192	2.736	100.000						

The results indicated that the correlation matrix has once again only 3 eigenvalues greater than 1, being presented in the table in a descending order: λ_1=2,7 λ_2=1,5 and λ_3= 1,2. The first principal component has the highest contribution consisting in 38% of the total gain of recovered information, followed by a 21% contribution of the second component and ending with a 17% more of the third component, leading to a total of **76%** of the variability of the initial space.

Table 18. **Rotated Component Matrix**[a]

	Component		
	1	2	3
Zscore(I1)	.856	.055	.034
Zscore(I2)	.772	.054	-.446
Zscore(I3)	.364	.814	.111
Zscore(I4)	.786	.084	-.203
Zscore(I5)	.720	-.095	.256
Zscore(I8)	-.038	.044	.946
Zscore(I7)	.228	-.882	.057

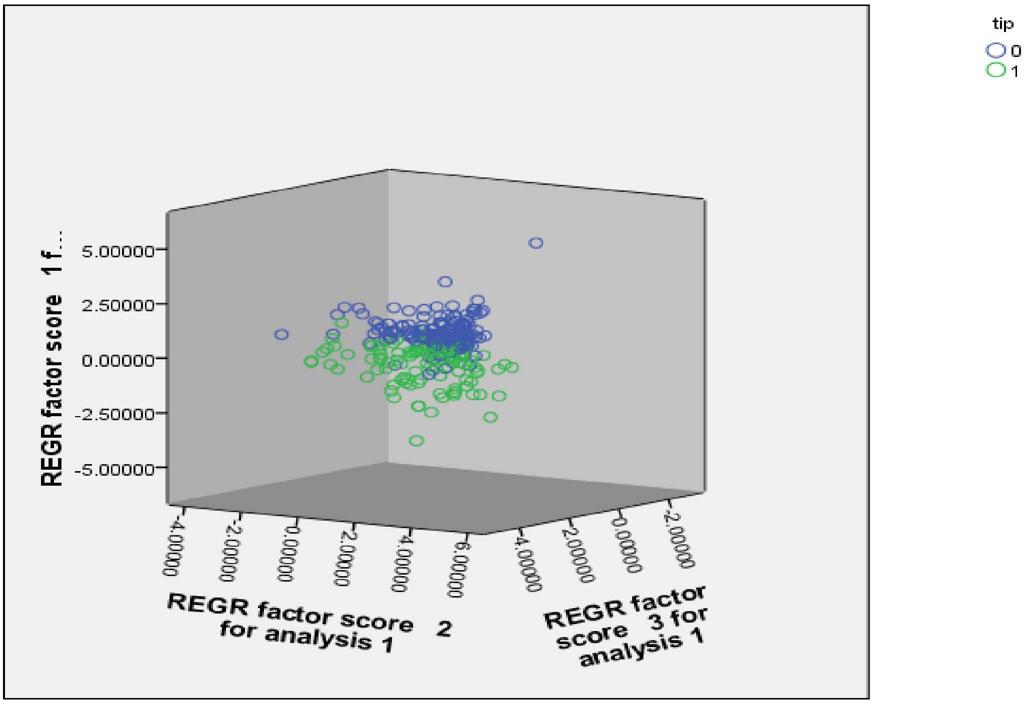
Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 4 iterations.

The first principal component is powerfully correlated to I1 (Profit margin), I2 (ROA) I4 (Profit per employee) and I5 (Operating Revenue per employee), the second component is highly correlated to and I3 (ROE) and I7 (Debts on Equity), while the third component is only strongly correlated with I8 (Total Debts on total Assets).

We can say that first component represents the profitability element, the second one is an Debts and Equity element, while the third principal component is a Debts and Assets element. When plotting the total sample on a 3-dimensional graphic described by the 3 principal components retained from the PCA, where the distressed companies are green colored and the non-distressed companies are blue colored, the results are quite similar to the previous analysis.

Fig. 5. Distressed and non-distressed companies on a 3 principal component space



To summaries, the results of the PCA can be presented in the following table:

Table 19. Summarize of the PCA

DATA SETS	Initial set of variables	Variables excluded	principal components retained	% of gain information
PANEL 1: first-year data set	I1, I2, I3, I4, I5, I8, I13 and I7	none	PC1: I1, I5, I13 PC2: I2, I4, I8 PC3: I3, I7	**72%**
PANEL 2: second-year data set	I1, I2, I3, I4, I5, I8 and I7	none	PC1: I1, I2, I14, I5 PC2: I3, I7 PC3: I8	**75%**
PANEL 3: third-year data set	I1, I2, I4, I5, I8, I9 and I11	I4	PC1: I1, I2, I5 PC2: I8, I9 PC3: I11	**75%**
PANEL 4: cumulative three-year data set	I1, I2, I3, I4, I5, I8, I13 and I7	I13	PC1: I1, I2, I4, I5 PC2: I3, I7 PC3: I8	**76%**

The PCA helped identifying the variables that are highly correlated to the retained principal components. Besides, by plotting the data sets on the principal component dimensionally reduced space the distressed companies tend to form a separate group from the rest of the companies, with only few exceptions, suggesting that trying to identify proper models using those financial ratios in order to correctly predict and classify the companies into "healthy" and "unhealthy" should therefore be possible.

5.3. CHAID Classification Tree

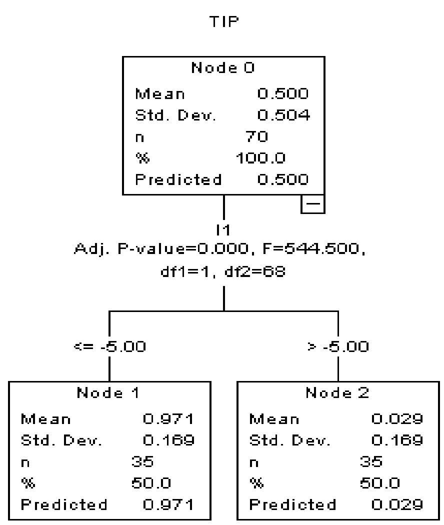
The study continued by building up and then testing a CHAID decision tree prediction model, closely following Zheng and Yanhui's (2007) approach. For this second part of the study SPSS 16.0 software was once again used. Since a decision tree has the ability to identify the best factors for the prediction and to establish consistent classification rules, all 14 initial ratios were included in the analysis for each of the 4 data sets.

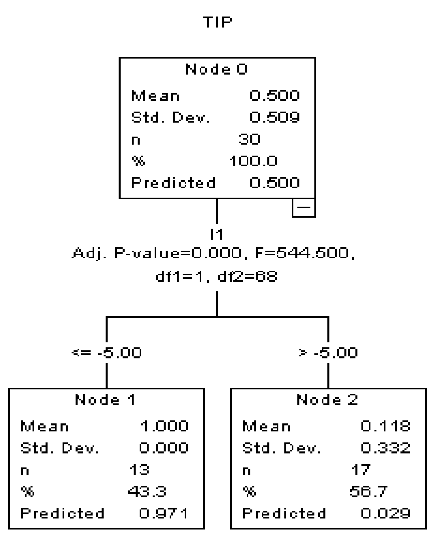
It is worth mentioning that the initial sample of 100 companies was divided into a 70% training sample and a 30% test sample. In order to measure the decision tree model efficiency, the out-of-sample performances were calculated and will then be compared to the other prediction models included in the study. The two alpha levels: α_{merge} and α_{split} values were set at a 0.05 level. To summarize it, the initial input for panels 1, 2 and 3 consisted in all 14 variables for a training sample of 70 companies, while the out-of-sample test consisted of the rest of 30 companies. In case of panel 4, which uses cumulative three-year data, 210 observations were used for training, while the rest of 90 more observations were used for out-of-sample tests.

PANEL 1: first- year data set

In this case, the specifications of the CHAID decision tree are: 7 minimum cases in parent node and 4 minimum cases in child nodes. The resulted CHAID decision tree has two layers and has split just one time, indicating that the only variable that is relevant to classify the initial sample of 70 companies into "healthy" and "unhealthy" companies is **Profit Margin (I1).** As noticing, the results indicated a profitability financial ratio to be the best predictor on this set of data, reaching therefore similar conclusions to those of Zheng and Yanhui's (2007).

Training decision tree **Test decision tree**





CHAID method was not only used to define the variables that can be used in the measurement of financial distress, but also to determine consistent classification rules. Since a decision tree generates a rule for each of its leaves, in our case there are only 2 classification rules, based on the values of the Profit margin financial ratio. More precisely, the decision tree classifies a company as being distress if the value of the Profit Margin is less than -5%. In the other case, the company is considered non-distressed. It is obvious that these rules are very sensitive to the initial data set. For this study, however, this classification rule leaded to a probability of **93,3%** correct out-of-sample prediction. The statistics are presented in table 20.

Table 20	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	35	35	70	15	15	30
incorect	1	1	2	2	0	2
corect	34	34	68	13	15	28
% incorect	2,9	2,9	2,9	13,3	0,0	6,7
% corect	97,1	97,1	**97,1**	86,7	100,0	**93,3**

PANEL 2: second- year data set

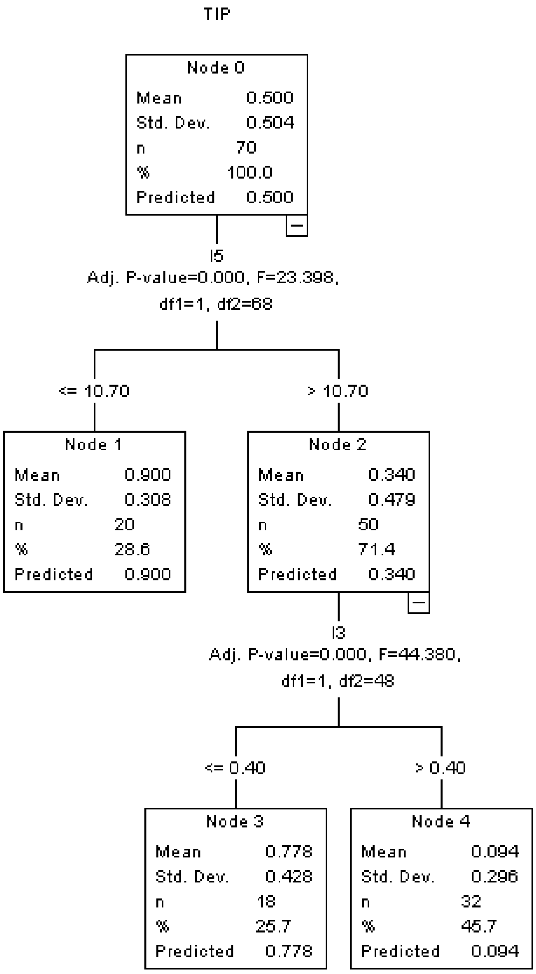
In this second case, when using financial ratios of the year 2007 to predict financial distress 2 years ahead, the specifications of the CHAID decision tree are: 30 minimum cases in parent node and 15 minimum cases in child nodes.

The resulted CHAID decision tree has three layers and has split two times, indicating that the two variables that are relevant to classify the initial sample of 70 companies into "healthy" and "unhealthy" companies when using the financial data of the year 2007 are **Operating Revenue per employee (I5)** and **Return on Equity (I3).** As noticing, the results indicated once again that profitability financial ratio tend to be the best predictors on this set of data. In this case there are 3 classification rules, based on the values of the Operating Revenue per employee (I5) and Return on Equity (I3). More precisely, the decision tree classifies a company as being distress if the value of the natural logarithm of Operating Revenue per employee is less than 10.7% or when it is greater than 10.7% but ROE is less than 0.4%. In the other case, the company is considered non-distressed. Based on this classification rules the tree correctly classified the companies into distress and non-distress with a probability of **86.7%**.

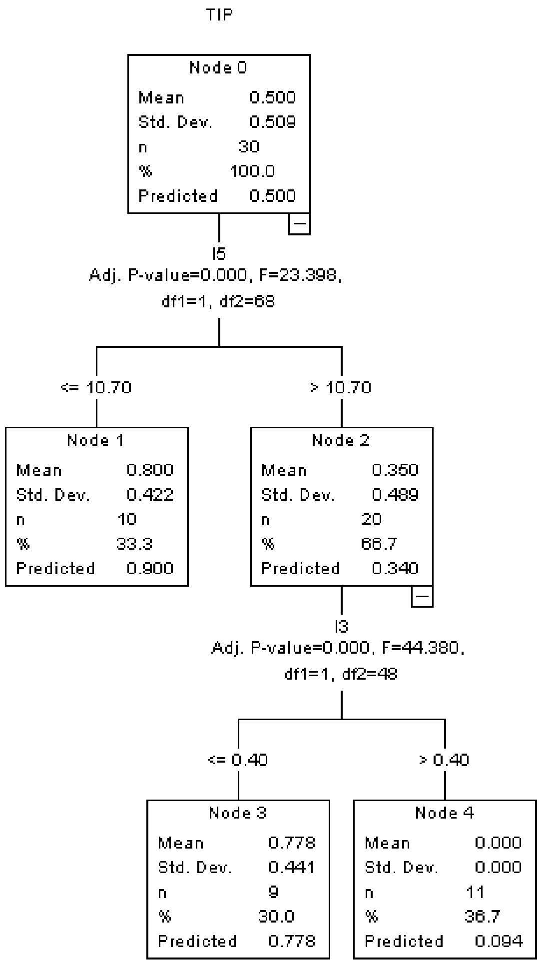
The statistics are also presented in the table below:

Table 21.	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	35	35	70	15	15	30
incorect	3	6	9	0	4	4
corect	32	29	61	15	11	26
% incorect	8,6	17,1	12,9	0,0	26,7	13,3
% corect	91,4	82,9	**87,1**	100,0	73,3	**86,7**

Training decision tree



Test decision tree



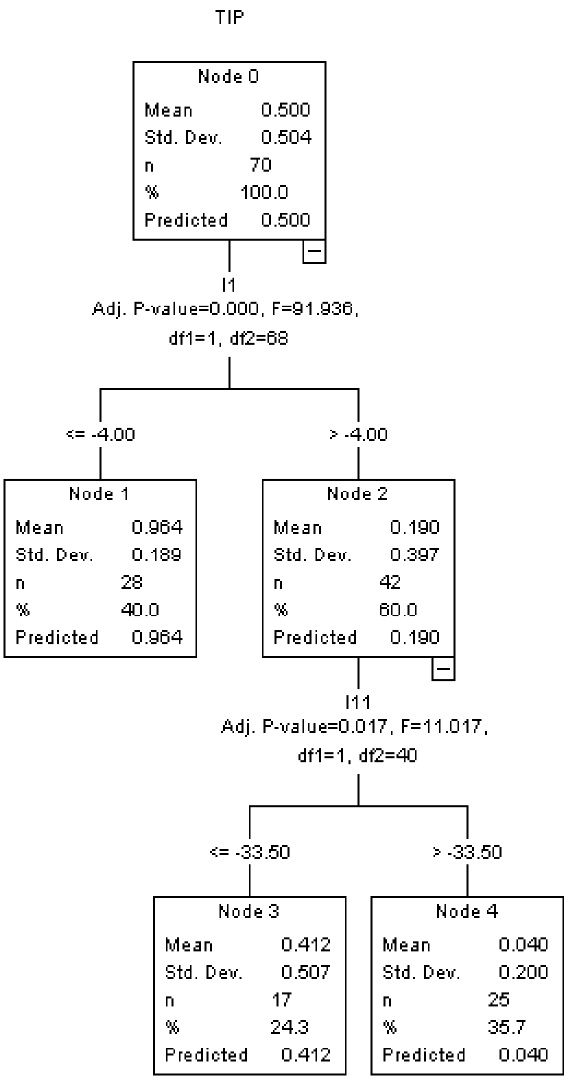
PANEL 3: third- year data set

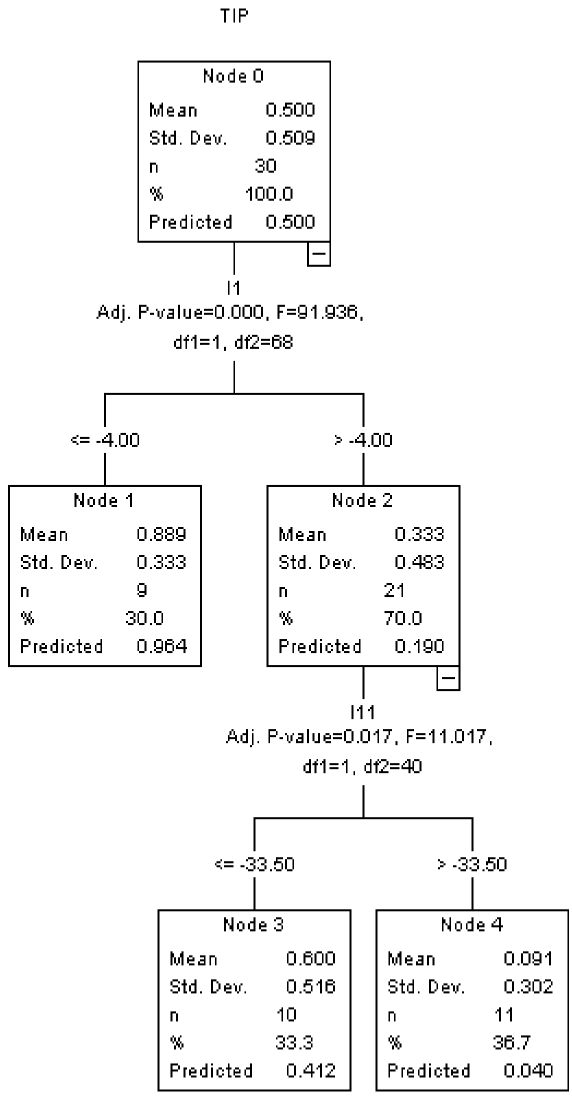
In the third case, when using financial ratios of the year 2006 to predict financial distress 3 years ahead, the specifications of the CHAID decision tree are: 30 minimum cases in parent node and 15 minimum cases in child nodes.

The resulted CHAID decision tree has three layers and has split two times, indicating that the two variables that are relevant to classify the initial sample of 70 companies into “healthy” and “unhealthy” companies when using the financial data of the year 2006 are **Profit Margin (I1)** and **Growth rate on net profit (I11).**

As noticing, the results indicated once again that profitability and growth financial ratios play the role as best predictors on this set of data. In this case there are also 3 classification rules, based on the values of the Profit Margin (I1) and Growth rate per profit (I11). More precisely, the decision tree classifies a company as being distress if the value of the Profit Margin is less than -4%. When Profit Margin is higher than -4% but the Growth rate on net profit is less than -33.5% the companies are considered non-distress, but the predicted value is 0.41, which is really close to the cutoff 0.5. That is why, the companies that have this predicted value should be analyzed with higher precaution, since might have chances to be incorrectly classified. The last classification rule considers a company as non-distressed with a predicted value of 0.04 in case the Profit Margin is higher than -4%, but the Growth rate on net profit higher than -33.5%.

Training decision tree **Test decision tree**





Based on this classification rules the tree correctly classified the companies into distress and non-distress with a probability of only **73.3%**. The explanation is given by the class of companies that are predicted non-distress, but have a prediction value of 0.41, which makes the results less accurate. The statistics are also presented in table 22.

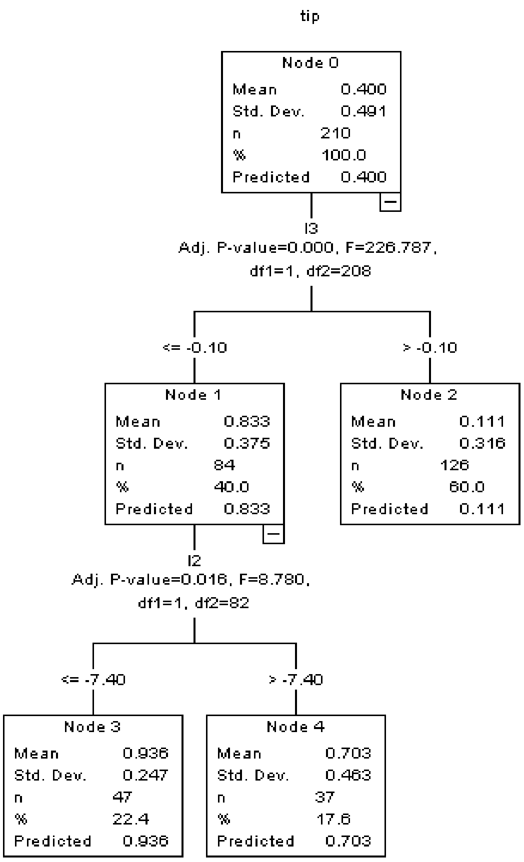
Table 22.	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	35	35	70	15	15	30
incorect	8	1	9	7	1	8
corect	27	34	61	8	14	22
% incorect	22,9	2,9	12,9	46,7	6,7	26,7
% corect	77,1	97,1	**87,1**	53,3	93,3	**73,3**

PANEL 4: cumulative three-year data set

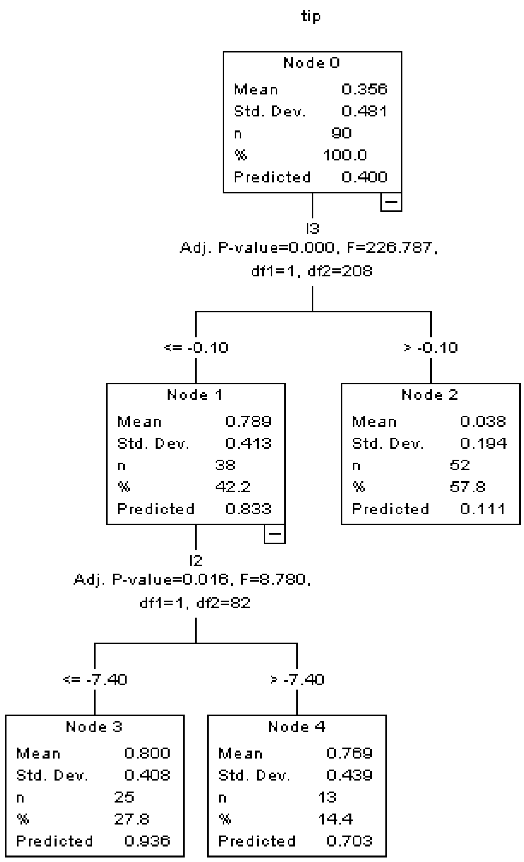
In the last case, when using financial ratios of the years 2006-2008 to predict financial distress 1 year ahead, the specifications of the CHAID decision tree are: 50 minimum cases in parent node and 25 minimum cases in child nodes.

The resulted CHAID decision tree is similar to the previous one, having as well three layers. However, in this case, when using cumulative three-year data set, the decision tree splits two times at **ROE (I3)** and **ROA (I2).** The results are also consistent to the theory, indicating once again that profitability financial ratios play the role as best predictors for financial distress when using CHAID decision tree.

Training decision tree



Test decision tree



There are also 3 classification rules, based on the values of the ROE (I3) and ROA (I2). First, a company is classified as non-distressed if I3 is higher than -0.1%. On the other hand, if I3 is less than -0.1%, a company is considered distressed, with two different predicted values, depending if I2 is higher or less -7.4%: 0.93 for which the certainty of the classification is higher, and 0.7 which might rise a few doubts. Once again, like in the previous decision tree rule, the results indicated that the companies that have this predicted value should be analyzed with higher precaution, since have more chances to be incorrectly classified. Based on this classification rules the tree correctly classified the companies into distress and non-distress with a probability of only **89%**. The statistics are presented in table 23.

Table 23.

	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	105	105	210	45	45	90
incorect	14	14	28	2	8	10
corect	91	91	182	43	37	80
% incorect	13,3	13,3	13,3	4,4	17,8	11,1
% corect	86,7	86,7	**86,7**	95,6	82,2	**88,9**

The results from the CHAID decision tree analysis are summarized in the table below:

Table 24. Summarize of CHAID models

DATA SETS	Variables selected	% in sample performance	% out-of-sample performance	Classification rules
PANEL 1: first-year data set	**I1**	**97,1%**	**93,3%**	If I1 >= -5=> prediction =0.97 If I1 < -5 => prediction = 0.0285
PANEL 2: second-year data set	**I5, I3**	**87,1%**	**87%**	If I5 <= 10.7 => prediction = 0.9 If I5> 10.7 and I3<=0.4 => prediction = 0.77 If I5> 10.7 and I3>0.4 => prediction= 0.094
PANEL 3: third-year data set	**I1, I11**	**87,1%**	**73,3%**	If I1<= -4 => prediction = 0.96 If I1> -4 and I11<= -33.5 => prediction=0.41 If I1> -4 and I11> -33.5 => prediction=0.04
PANEL 4: cumulative three-year data set	**I3, I2**	**86,7%**	**89%**	If I3 > -0.1=> prediction= 0.11 If I3<= -0.1 and I2> -7.4 => prediction=0.7 If I3<= -0.1 and I2<= -7.4 => prediction=0.94

We notice that in all four cases, the profitability ratios are best predictors, while when using financial data of the year 2006 to predict distress 3 years ahead both a profitability and a growth ability ratio proved to be relevant for the distress prediction problem. The results are consistent to those obtained in other similar studies (**Zheng and Yanhui** (2007) and **Koyuncugil A. S. and N. Ozgulbas** (2007)).

Best out-of-sample results are obtained when using first-year data, but high forecasting accuracy is also obtained when using cumulative three-year data and second-year data. The lowest accuracy is, however, obtained when using panel 3, suggesting that a 3-year ahead distress prediction is less efficient.

A final test with CHAID models was then conducted, when using the 3 principal components obtained from the PCA as inputs for the decision trees, for each of the 4 data sets. The prediction results ar presented below:

Table 25. Summarize of CHAID models using principal components as variables

DATA SETS	principal components selected	% in sample	% out of sample
PANEL 1: first-year data set	1	**88,6%**	**93,3%**
PANEL 2: second-year data set	1,2	**91,4%**	**96,7%**
PANEL 3: third-year data set	1,2	**87,1%**	**70,0%**
PANEL 4: cumulative three-year data set	1,2	**84,3%**	**84,4%**

We notice that the prediction results improved only when using the first two principal components for the second data set, for which the out-of-sample prediction power reached **96,7%** .

5.4. The Logistic and the Hazard Model

The financial distress prediction study continues with a third approach, based on econometric theory. As already presented in the literature review concerning the distress prediction issue, there are quite a large number of studies focused on the logistic and hazard models in order to predict the probabilities to which a company may become distress in the following periods. Based on Shumway's (2001) theory, the logistic model is the classical dichotomous static model, which uses only one year financial data for each company of the initial set of data, while a multi-period logit model considers each annual financial ratio of a company to be a distinct observation, being therefore, time invariant.

The study is once again divided into 4 parts, by distinctly analyzing each set of data: a first-year data set, a second-year data set, a third-year data set and a cumulative three-year data set. In the first three panels, since considering only one year financial data for each company, a **single-period logit model** was estimated in order to classify and to predict financial distress. When using the forth panel that includes financial data for all three years: 2006–2008, however, two hazard models were estimated: the first **hazard model having time varying covariates but time invariant baseline hazard function** and the second **hazard model having time varying covariates and also time varying baseline hazard function**, described through macroeconomic variables, as suggested by the Nam, Kim, Park and Lee (2008).

Once again, the initial sample was divided into a 70% training sample and a 30% forecasting sample. In order to measure the econometric binomial models efficiency, the out-of-sample performances was calculated and then compared in order to find the model that best predicts financial distress. The initial input for panels 1, 2 and 3 consisted in all variables that have the highest ability to differentiate between financially distressed and non-distressed companies due to their mean differences for a training sample of 70 companies, while the out-of-sample forecast consisted of the rest of 30 companies, while in case of panel 4, which uses cumulative three-year data, 210 observations were used for training, while the rest of 90 were used for out-of-sample prediction tests.

The following steps were taken in order to find the best logistic model for distress prediction:

- First a backward looking procedure was followed: starting by estimating a logistic model with all the variables (that passed the mean difference tests) included, followed by a step by step procedure of excluding the variables that are not significant and by choosing the model with lowest Akaike and Schwartz values.
- Then a second approach was taken, consisting in a forward looking method, that started with one variable, for which the Akaike value was the smallest and followed by a step by step test of each of the remaining variables that best passes the *Omitted Variables Likelihood Ratio Test,* which considers the following null hypothesis:

  H0: $y_i = \beta_1 * x_1$, that is $\beta_2 = 0$.

  H1: $y_i = \beta_1 * x_1 + \beta_2 * x_2$

  If the p value is less than 0.05 then the variable x_2 is considered to be significant and should be included in the model.
- Then, for each resulting model, each coefficient sign is checked to see if it corresponds to the economic theory and in case of a different sign, the corresponding value is dropped.
- Lastly, the remaining models (in case of more than just one model) are compared based on the following criteria: *out-of-sample performance, McFadden value, LR value, AIC value, the goodness of fit Test (H-L Statistics) and total gain in comparison to the simple constant model and the best model is selected.*

PANEL 1: first- year data set

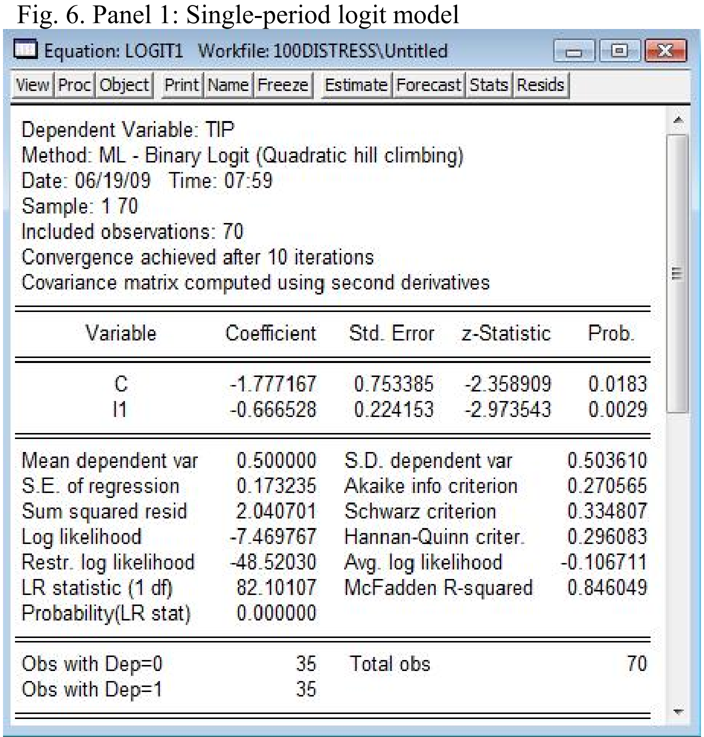
I first considered the data set consisting in the financial ratios of the year 2008 for the 100 Romanian listed companies that passed the mean difference statistic tests. When conducting the backward looking procedure it led to a single variable logistic model, best described by variable **I1**. On the other hand, when conducting the forward looking procedure it resulted that the model should include variable **I4**, but in which case the intercept was not even 10% significant. To conclude, the only valid logistic model that resulted for the case of first-year data set is a model that only includes variable **I1**, that is **Profit Margin**. The distress prediction model constructed from the estimation of a single period logit model has the following logit equation:

$$p_i = P(y_i = 1) = \frac{1}{1 + e^{-(-1{,}777 - 0{,}666 * I1)}}$$

If we look back at the second part of the study, however, were a CHAID decision tree model was built, we can see that the results are consistent since both models identified variable I1 to be the only relevant predictor for one year ahead distress prediction.

From the EViews estimation output window presented below, we see that instead of using the t statistic to evaluate the statistical significance of a coefficient the (standard normal) Z statistic is used. The reason is that when using the method of maximum likelihood, which is generally a large-sample method, the estimated standard errors are asymptotic. Besides, the theory argues that if the sample size is reasonably large, the t distribution converges to the normal distribution.

Fig. 6. Panel 1: Single-period logit model


Equation: LOGIT1 Workfile: 100DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/19/09 Time: 07:59
Sample: 1 70
Included observations: 70
Convergence achieved after 10 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.777167	0.753385	-2.358909	0.0183
I1	-0.666528	0.224153	-2.973543	0.0029

Mean dependent var	0.500000	S.D. dependent var	0.503610
S.E. of regression	0.173235	Akaike info criterion	0.270565
Sum squared resid	2.040701	Schwarz criterion	0.334807
Log likelihood	-7.469767	Hannan-Quinn criter.	0.296083
Restr. log likelihood	-48.52030	Avg. log likelihood	-0.106711
LR statistic (1 df)	82.10107	McFadden R-squared	0.846049
Probability(LR stat)	0.000000		

Obs with Dep=0	35	Total obs	70
Obs with Dep=1	35		

Although the estimated logistic model is only described by variable I1, for which the coefficient sign is consistent to the theory that says that the lower the Profit Margin is, the higher the chances to financial distress are, we notice that the McFadden R-squared value is quite high (**84.6**%). Moreover, the Likelihood ratio test indicates that the model is valid and the Akaike and Schwartz values are low.

Several other tests were afterwards made in order to check the validity and efficiency of the model which are presented in tables 6-8 in ANNEXES. The residual correlogram shows no correlation between residuals, while the normality hypothesis is no longer necessary for the logistic model. Next, the *Expectation Predicted Table* was generated, in order to see how the training process was made and just how much gain the model brings in comparison to the simple constant logistic model. In table 6 in ANNEXES one can see that the model correctly predicted 97% in sample and the total gain in comparison to the simple constant model is of 47%. The goodness of fit Test (H-L Statistics) of 0.59 indicates that the model is indeed valid.

The next step of the econometric analysis consists in testing the model's out-of-sample forecasting performaces. It resulted that this model predicted Romanian financial distress with a probability of **100%**.

Table 26.	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	35	35	70	15	15	30
incorect	1	1	2	0	0	0
corect	34	34	68	15	15	30
% incorect	2,9	2,9	2,9	0,0	0,0	0,0
% corect	97,1	97,1	**97,1**	100,0	100,0	**100**

PANEL 2: second- year data set

When using the financial ratios of the year 2007 for the 100 Romanian listed companies to predict distress 2 years ahead, some new single-period logistic models were estimated.

When conducting both the backward looking and the forward looking procedure, several logistic models were obtained. However, most of them included the variable I14, representing Company size with the wrong sign, which invalidated the results. After several comparisons between the remaining models, it led to a multivariable logistic model, best described by variables **I3, I5 and I8**. The distress prediction model constructed from the estimation of this single period logit model has the following logit equation:

$$p_i = P(y_i = 1) = \frac{1}{1 + e^{-(22{,}57 - 0{,}02 * I3 - 2{,}139 * I5 + 0{,}0334 * I8)}}$$

If we look back at the second part of the study again, to the CHAID decision tree model built for this panel, we notice that once again the results are quite similar, since the CHAID tree also identified I3 and I5 as best predictors. In the logistic model, however, variable I8, representing Total Debts on Total Assets was also found to be significant for a two-year ahead prediction of financial distress.

Further on, from the EViews estimation output window presented in fig. 7, we notice that the signs of the coefficients do correspond to the economic theory. To be more specific, the higher the ROE and the Operating Revenue per employee are, the lower the chances for a company to become distress are. On the other hand, if a company's Total Debts on Total Assets tend to grow, then the company has higher chances to become distress.

Although the McFadden R-squared value is only **37**%, the Likelihood ratio test indicates that the model is valid. The *Expectation Predicted Table* indicated that the model's total gain in comparison to the simple constant model is of 29% and the probability of the goodness of fit Test is of 0,86, which indicates that the model is indeed valid. Both results are presented in tables 9-10 in ANNEXES.

Fig. 7. Panel 2: Single-period logit model

Equation: UNTITLED Workfile: 2007\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 01:41
Sample: 1 70
Included observations: 70
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	22.57301	6.459198	3.494708	0.0005
I3	-0.020148	0.009676	-2.082219	0.0373
I5	-2.138905	0.592367	-3.610778	0.0003
I8	0.033396	0.012510	2.669627	0.0076

Mean dependent var	0.500000	S.D. dependent var	0.503610
S.E. of regression	0.394996	Akaike info criterion	0.988425
Sum squared resid	10.29744	Schwarz criterion	1.116911
Log likelihood	-30.59488	Hannan-Quinn criter.	1.039461
Restr. log likelihood	-48.52030	Avg. log likelihood	-0.437070
LR statistic (3 df)	35.85084	McFadden R-squared	0.369442
Probability(LR stat)	8.05E-08		

Obs with Dep=0	35	Total obs	70
Obs with Dep=1	35		

The next step of the econometric analysis consists in testing the model's out-of-sample forecasting performaces. It resulted that this model predicted 2 years ahead Romanian financial distress with a probability of **76,7**%.

Table 27.	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	35	35	70	15	15	30
incorect	9	6	15	3	4	7
corect	26	29	55	12	11	23
% incorect	25,7	17,1	21,4	20,0	26,7	23,3
% corect	74,3	82,9	**78,6**	80,0	73,3	**76,7**

PANEL 3: third- year data set

Further on was considered the case of the third-year data set, consisting in the financial ratios of the year 2006 for the 100 Romanian listed companies. When conducting both the backward looking and the forward looking procedure, several single-period logistic models were obtained. After some comparisons between the best remaining models, presented in tables 11-15 in ANNEXES, it led to a multivariable logistic model, best described by variables **I2 and**

I5. The distress prediction model constructed from the estimation of this single period logit model has the following logit equation:

$$p_i = P(y_i = 1) = \frac{1}{1 + e^{-(15{,}2 - 1{,}39 * I5 - 0{,}14 * I2)}}$$

In this case, when comparing the results to the CHAID model we notice that the chosen predictors are different from those identified by the decision tree. However, when looking back at the mean differences tests, we see that variables I2 and I5 are two of the variables that have the most significant mean differences.

Further on, from the EViews estimation output window presented in fig. 8, we notice that the signs of the coefficients correspond to the economic theory. To be more specific, the higher the ROA and Operating Revenue per employee are, the lower the chances for a company to become distress are. On the other hand, if a company's Total Debts on Total Assets tend to grow, then the company has higher chances to become distress.

Although the McFadden R-squared value is only **41**%, the Likelihood ratio test indicates that the model is valid. The *Expectation Predicted Table* indicated that the model's total gain in comparison to the simple constant model is of 36% and the probability of the goodness of fit Test is of 0,081, which indicates that the model is valid. Both results are presented in tables 11-12 in ANNEXES.

Fig. 8. Panel 3: Single-period logit model

Equation: UNTITLED Workfile: 2006_DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 15:42
Sample: 1 70
Included observations: 70
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	15.20659	6.621508	2.296545	0.0216
I5	-1.391093	0.602248	-2.309833	0.0209
I2	-0.141076	0.052150	-2.705218	0.0068

Mean dependent var	0.500000	S.D. dependent var	0.503610
S.E. of regression	0.362683	Akaike info criterion	0.907385
Sum squared resid	8.813093	Schwarz criterion	1.003750
Log likelihood	-28.75849	Hannan-Quinn criter.	0.945662
Restr. log likelihood	-48.52030	Avg. log likelihood	-0.410836
LR statistic (2 df)	39.52362	McFadden R-squared	0.407290
Probability(LR stat)	2.62E-09		

Obs with Dep=0	35	Total obs	70
Obs with Dep=1	35		

The next step of the econometric analysis consists in testing the model's out-of-sample forecasting performaces. It resulted that this model predicted 3 years ahead Romanian financial distress with a probability of **73,3**%.

Table 28.	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	35	35	70	15	15	30
incorect	7	3	10	5	3	8
corect	28	32	60	10	12	22
% incorect	20,0	8,6	14,3	33,3	20,0	26,7
% corect	80,0	91,4	**85,7**	66,7	80,0	**73,3**

PANEL 4: cumulative three- year data set

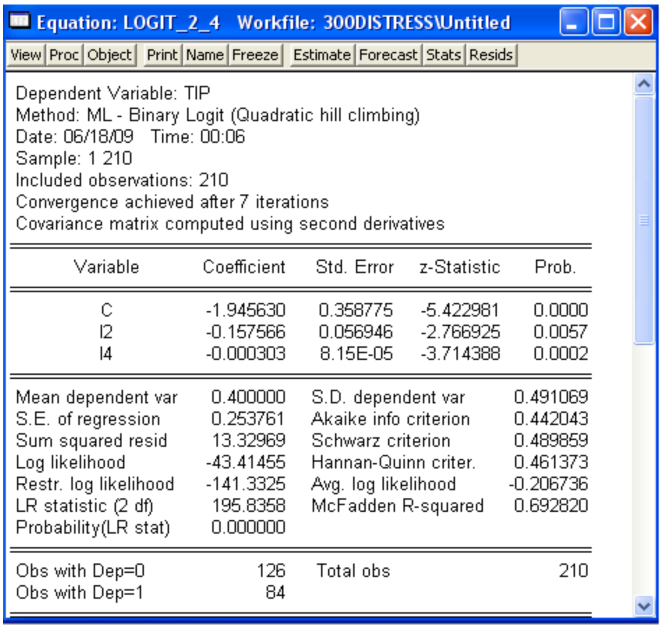
The last case considered used the cumulative three-year data set in order to predict distress 1 year ahead. The study implied estimating both a hazard model having time varying covariates but time invariant baseline hazard function and a hazard model having time varying covariates and also time varying baseline hazard function, described by macroeconomic variables. After following the step by step procedures in order to find the best hazard model with time invariant baseline hazard function, a multivariable logistic model, best described by variables **I2 and I4** resulted. The distress prediction model constructed from the estimation of a hazard model with time invariant baseline hazard function is described by the equation:

$$p_i = P(y_i = 1) = \frac{1}{1 + e^{-(-1,95-0,16*I2-0,0003*I4)}}$$

In this case, when comparing the results to the CHAID model we notice that the I2 was also considered a significant predictor by the decision tree model. However, the first hazard model also identified variable I4 to be required in the prediction econometric model.

From the EViews estimation output window presented in fig. 9, we notice that the signs of the coefficients correspond to the economic theory. To be more specific, the higher the ROA and Profit per employee are, the lower the chances for a company to become distress are.

Fig. 9. Panel 4: Hazard model with time invariant baseline hazard function


Equation: LOGIT_2_4 Workfile: 300DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/18/09 Time: 00:06
Sample: 1 210
Included observations: 210
Convergence achieved after 7 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.945630	0.358775	-5.422981	0.0000
I2	-0.157566	0.056946	-2.766925	0.0057
I4	-0.000303	8.15E-05	-3.714388	0.0002

Mean dependent var	0.400000	S.D. dependent var	0.491069
S.E. of regression	0.253761	Akaike info criterion	0.442043
Sum squared resid	13.32969	Schwarz criterion	0.489859
Log likelihood	-43.41455	Hannan-Quinn criter.	0.461373
Restr. log likelihood	-141.3325	Avg. log likelihood	-0.206736
LR statistic (2 df)	195.8358	McFadden R-squared	0.692820
Probability(LR stat)	0.000000		

Obs with Dep=0	126	Total obs	210
Obs with Dep=1	84		

The validity of the model is also suggested by the McFadden R-squared value of **69**%, the Likelihood ratio test, the model's total gain in comparison to the simple constant model of 31% and the probability of the goodness of fit Test of 0,065. The last 2 tests are presented in tables 16-17 in ANNEXES.

When testing the model's out-of-sample forecasting performaces, it resulted that this model predicted 1 year ahead Romanian financial distress with a high probability of **91.1**%.

Table 29.

	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	105	105	210	45	45	90
incorect	11	8	19	1	7	8
corect	94	97	191	44	38	82
% incorect	10,5	7,6	9,0	2,2	15,6	8,9
% corect	89,5	92,4	**91,0**	97,8	84,4	**91,1**

For the second case of the hazard model with time varying baseline hazard function, the following two macroeconomic variables were used for estimating the baseline hazard function: *the change in lending rate* and *the change in EURO/RON exchange rate*. Although both models were valid, the choice for the hazard model with the baseline hazard function described by the change in EURO/RON exchange rate was based on the following reasons:

- The out-of-sample precision was higher (92.2% versus **90%**)
- The McFadden R squared value was also higher (72% versus 71%)
- The Akaike and Schwarz criterion were lower (0.41 versus 0.42 and 0.475 versus 0.49)

All tests are presented in tables 19 – 23 in ANNEXES, while the chosen model is in fig.10.

Fig. 10. Panel 4: Hazard model with time varying baseline hazard function

Equation: HAZARD2_4_CHANGE_EUR Workfile: 300DI...

'iew Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 18:07
Sample: 1 210
Included observations: 210
Convergence achieved after 8 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
CHANGE_EUR	0.129721	0.047878	2.709395	0.0067
C	-2.254988	0.431613	-5.224558	0.0000
I2	-0.195007	0.063609	-3.065688	0.0022
I4	-0.000329	8.67E-05	-3.790368	0.0002

Mean dependent var	0.400000	S.D. dependent var	0.491069
S.E. of regression	0.241901	Akaike info criterion	0.411215
Sum squared resid	12.05428	Schwarz criterion	0.474969
Log likelihood	-39.17753	Hannan-Quinn criter.	0.436988
Restr. log likelihood	-141.3325	Avg. log likelihood	-0.186560
LR statistic (3 df)	204.3098	McFadden R-squared	0.722799
Probability(LR stat)	0.000000		

Obs with Dep=0	126	Total obs	210
Obs with Dep=1	84		

The distress prediction model constructed from the estimation of a hazard model with time varying baseline hazard function is described by the following equation:

$$p_i = P(y_i = 1) = \frac{1}{1 + e^{-0,13*\alpha(t)-(-2,25-0,195*I2-0,0003*I4)}}$$

As noticing, when testing the model's out-of-sample forecasting performaces, resulted a high accuracy of **92.2**% for a 1 year ahead prediction of the Romanian financial distress.

Table 30.

	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	105	105	210	45	45	90
incorect	8	8	16	1	6	7
corect	97	97	194	44	39	83
% incorect	7,6	7,6	7,6	2,2	13,3	7,8
% corect	92,4	92,4	**92,4**	97,8	86,7	**92,2**

The results from the logistic and hazard models are summarized in the table below:

Table 31. Summarize of the Logit and Hazard models

DATA SETS	% in sample performance	% out-of-sample performance	prob. H-L Test	Mc Fadden R squared	% gain vs the constant model	Variables coefficients	expected sign
PANEL 1: first-year data set single-period logit model	**97,10%**	**100%**	**0,99**	**85%**	**47%**	**I1 : -0,66 (0,0029)** **C : -1,77 (0,0183)**	**(-)**
PANEL 2: second-year data set single-period logit model	**78,60%**	**77%**	**0,86**	**37%**	**29%**	**I3 : -0,002 (0,037)** **I5 : -2,139 (0,0003)** **I8 : 0,033 (0,0076)** **C : 22,57 (0,0005)**	**(-)** **(-)** **(+)**
PANEL 3: third-year data set single-period logit model	**85,70%**	**73,30%**	**0,08**	**41%**	**36%**	**I5 :-1,391 (0,0209)** **I2: - 0,141 (0,0068)** **C: 15,21 (0,0216)**	**(-)** **(-)**
PANEL 4: cumulative three-year data set: hazard model with invariant baseline fct.	**91%**	**91%**	**0,07**	**69%**	**31%**	**I2 : -0,1576 (0,0057)** **I4 : -0,0003 (0,0002)** **C : -1,945 (0,000)**	**(-)** **(-)**
PANEL 4: cumulative three-year data set: hazard model with time varying baseline fct	**92,40%**	**92%**	**0,53**	**73%**	**32%**	**I2: -0,195 (0,000)** **I4 : -0,00032 (0,0002)** **ch_eur: 0,129 (0,007)** **C : -2,255 (0,000)**	**(-)** **(-)** **(+)**

We notice that when using panel 1, panel 3 and panel 4, the profitability ratios are best predictors, while when using financial data of the year 2007 to predict distress 2 years ahead also a solvency ratio (*Debts on Equity* – I8) proved to be relevant for the distress prediction problem. The coefficients signs are consistent to the theory for each data set considered. Moreover, the conclusions regarding the prediction improvement of the hazard model with time varying baseline hazard function incorporating a macroeconomic variable are similar to those obtained in the recent studies (**Nam, Kim, Park and Lee** (2008), **Abdullah, Halim, Ahmad and Rus** (2008)). Best out-of-sample results are obtained when using first-year data, but high forecasting accuracy is also obtained when using cumulative three-year data and second-year data. The lowest accuracy is obtained when using panel 3, suggesting once again that a 3 years ahead distress prediction is less efficient.

A final test with logit models was then conducted, when using the 3 principal components obtained from the PCA as inputs for the econometric models, for each of the 4 data sets. The results ar presented below:

Table 32. Summarize of the Logit and Hazard models when using principal components

DATA SETS	principal components selected	% in sample	% out of sample
PANEL 1: first-year data set	1, 3	**90.0%**	**90.0%**
PANEL 2: second-year data set	1, 2	**94,3%**	**96,7%**
PANEL 3: third-year data set	no valid model		
PANEL 4: cumulative three-year data set	1	**87,1%**	**86,7%**

Similar to the CHAID results, the prediction performance improved only when using the principal components for the second data set, for which the out-of-sample prediction power reached **96,7%** .

5.5. Artificial Neural Network

Before feeding the data into the ANN the four data sets were transformed as follows: all the positive values of each predictor were scaled to the interval [0, 1], while all the negative values of each predictor were scaled to the interval [-1, 0]. A program using a feed forward backpropagation network was then implemented in MATLAB, that can be found in ANNEX ANN. The network had one input layer, one hidden layer (with only one neuron) and one output layer and was trained on the same data sets as the previous methods. The training stage lasted for 2000 iterations or until the error was below a specified threshold (10^{-15}).

Two types of tests were performed. The first type of tests used all the 14 predictors as inputs to the ANN, while the second type of tests were based on the hybrid ANN method, which includes as predictors only those variables that were highlighted as being relevant by the previous CHAID, LOGIT and HAZARD models and are marked as ANN – Ii,..Ik , where Ii,., Ik are the predictors from the previous models.

The results for the ANN models are summarized in table 33.

Table 33. Summarize of the ANN

DATA SETS	Initial set of variables for ANN	no. neurons	% in sample	% out of sample
PANEL 1: first-year data set	all 14	1	**100,00%**	**90,00%**
PANEL 2: second-year data set	all 14	1	**100,00%**	**100,00%**
PANEL 3: third-year data set	all 14	1	**100,00%**	**66,70%**
PANEL 4: cumulative three-year data set	all 14	1	**98,60%**	**88,90%**

When using ANN, the accuracy changes compared to the previous CHAID, logistic and hazard models. Looking at the out-of-sample performances, we notice that when using second-year data set, the ANN model including all 14 variables perfectly predicts the financial distress, proving therefore, to be extremely efficient. The main disadvantage consists in the fact that it does not tell anything about best predictors and the model is extremely difficult to build up and to interpret. Good prediction results are also obtained when using panel 1 and panel 4. However, when using third-year data set to predict distress 3 years ahead, it performs quite poorly, by only reaching a predicting accuracy of 67%.

The results for the second tests regarding the hybrid ANN models are summarized in the following table:

Table 34. Summarize of the hybrid ANN

DATA SETS	type of hybrid ANN	no. neurons	% in sample	% out of sample
PANEL 1: first-year data set	ANN - I1	1	**98,6%**	**100,0%**
PANEL 2: second-year data set	ANN - I3, I5	1	**91,4%**	**100,0%**
PANEL 3: third-year data set	ANN - I1, I11	1	**87,1%**	**73,3%**
PANEL 3: third-year data set	ANN - I2, I5	1	**85,7%**	**76,7%**
PANEL 4: cumulative three-year data set	ANN - I2, I4	1	**93,3%**	**91,1%**
PANEL 4: cumulative three-year data set	ANN - I2, I3	1	**90,5%**	**90,0%**

In this case hybrid ANNs perform better out-of-sample than the simple ANN when using panel 1 and panel 3 and makes no improvements when using panel 4 and panel 2. However, the in-sample performances are in these two cases lower.

6. CONCLUSIONS

The purpose of this study was to build up several early warning models for the Romanian financial distressed companies, using the following methodologies and models: PCA, CHAID models, Logit and Hazard models as well as ANN and Hybrid ANN and then to be able to conclude not only which are the best financial distress prediction models but also the best financial predictors for the Romanian listed companies sample. Since 4 distinct data sets were analyzed, the conclusions also had to be reached separately.

When using only the financial ratios of the year 2008 to predict distress 1 year ahead, the results showed that the best financial distress predictor is **Profit Margin** and the best prediction models are: single-period logit model and hybrid ANN – I1 with a 100% out-of-sample accuracy. Since the hybrid ANN-I1 actually uses the predictors highlighted from a single-period first estimation, I conclude that when using panel 1, the single period logit model is more suitable to be used. The perfect prediction accuracy might be explained by the fact that in the last financial year -2008- the financial crisis effects were more intense and therefore the impact upon the distressed companies was greater, which made the prediction easier.

In the second case, when using the financial data of the year 2007 to predict distress 2 years ahead, the parametric methods did not lead to any higher prediction accuracy than 87% reached by the CHAID model. For this data set, the best prediction model was the ANN that used **all 14** ratios and had an out-of-sample accuracy of 100%, but which tells nothing about which predictors might be more useful in the financial distress prediction.

When using the financial data of the year 2006 to predict distress 3 years ahead, 4 best prediction models were found: the single-period logistic model, the CHAID model, the hybrid ANN–I1,I11 and the hybrid ANN– I2,I5, having as predictors the following pairs: (**Profit Margin, Growth rate on net profit)** and **(ROA, Operating Revenue per employee**) with an out-of-sample accuracy of 73.3%. In this situation, it is hard to choose one model from them all. What I could do however is to consider that the two hybrid ANNs are less suitable to be used, since they reach the same prediction accuracy but require building up first the single-period logit model or the CHAID model in order to select the variables that are best predictors.

In the last case, when using all financial ratios for the years 2006-2008 to predict distress 1 year ahead, the hazard model with time varying baseline hazard function having the following predictors: (**ROA, Profit per employee,** exchange rate) resulted as best prediction model with an out-of-sample accuracy of 92%.

Besides, by investigating the out-of-sample forecasting performances of the hazard model with time varying baseline hazard function incorporating a macroeconomic variable compared to the results of both traditional single-period logit models and also to the hazard model with time invariant baseline hazard function, I demonstrated the improvements produced when allowing temporal and macroeconomic dependencies based on the change of EURO/RON exchange rate. The conclusions are also similar to those from the studies made by **Nam, Kim, Park and Lee** (2008) and **Abdullah, Halim, Ahmad and Rus** (2008).

The results are indeed consistent with the theory and also to the previous studies and showed that it is indeed possible to generate a few years ahead warning signals for the Romanian distressed companies with a quite high accuracy when using the appropriate prediction model and profitability, growth ability and solvency ratios.

I believed that the results of this study are not only useful for any company to survive and to take early actions as a precaution, but also for any bank, investor and regulatory authority. The inconvenience however of these prediction models is that they highly depend on the data used in the analysis and perhaps, in case of a larger sample of data the models might behave differently. Even so, the conclusions are quite encouraging. Since the out-of-sample forecast accuracy of the estimated models of this study lies in the range of 73%-100%, it indicates that the early warning models for the Romanian listed companies are quite efficient.

A future concern regards the ability of predicting Romanian bankrupt companies by adopting a similar approach, but for which the required data were momentary not available.

7. REFERENCES

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ANNEXES

Table 1. PANEL 1: first-year data set: Correlation matrix

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14
I1	1.000	**.572**	.254	**.587**	**.565**	.119	.041	-.058	.160	-.088	-.078	.010	.407	.167
I2		1.000	.224	**.528**	.416	.139	.258	**-.469**	.155	.178	-.140	.122	.256	.144
I3			1.000	.193	.228	-.016	**-.554**	.167	-.041	.000	.028	.010	.085	.117
I4				1.000	.381	.146	.077	-.275	.366	.024	.075	.024	.226	.017
I5					1.000	-.022	.120	.027	.261	.419	.126	.066	.378	.463
I6						1.000	-.067	-.357	**.504**	.260	-.245	.155	-.100	-.050
I7							1.000	-.108	.038	.059	-.027	.028	.097	.034
I8								1.000	-.251	-.245	.205	-.162	-.058	.142
I9									1.000	**.442**	-.005	-.008	-.067	-.034
I10										1.000	.015	.319	-.052	.413
I11											1.000	.036	.168	.124
I12												1.000	.122	.114
I13													1.000	.124
I14														1.000

Table 2. PANEL 2: second-year data set: Correlation matrix

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14
I1	1.000	**.603**	.237	**.646**	**.531**	-.077	.000	.028	.090	-.114	-.003	.053	.123	.164
I2		1.000	.385	**.633**	.411	.017	.075	-.280	.067	.074	.228	.166	.295	.108
I3			1.000	.264	.098	-.014	**-.487**	-.063	-.017	-.036	.122	-.015	.008	-.076
I4				1.000	.248	-.383	-.012	-.055	-.004	-.188	.090	.125	.163	-.091
I5					1.000	.154	.162	.039	.386	**.536**	-.030	.185	.202	**.491**
I6						1.000	-.060	-.355	**.588**	**.462**	.036	-.027	-.244	.028
I7							1.000	.154	.042	.115	-.066	.040	.032	.156
I8								1.000	-.142	-.226	-.183	-.098	-.026	.142
I9									1.000	**.528**	-.072	.144	-.129	-.014
I10										1.000	.029	.382	.125	.380
I11											1.000	-.005	.116	-.007
I12												1.000	.262	.234
I13													1.000	.124
I14														1.000

Table 3. PANEL 3: third-year data set: Correlation matrix

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14
I1	1.000	**.526**	.261	**.732**	**.527**	.193	.151	.018	.153	-.198	-.036	-.439	.110	.097
I2		1.000	.446	**.751**	.372	.196	.160	-.318	.184	.154	-.011	.000	.335	.041
I3			1.000	.342	.316	.007	-.314	.266	-.061	.121	.007	-.030	.322	.184
I4				1.000	**.516**	.116	.218	-.053	.250	.036	-.015	-.105	.255	.100
I5					1.000	.088	.253	.070	.343	.423	.266	-.268	.377	**.476**
I6						1.000	-.079	-.355	**.473**	.252	-.083	-.113	-.110	-.069
I7							1.000	.087	.049	.038	.112	.004	.057	.143
I8								1.000	-.268	-.245	.063	-.116	-.069	.196
I9									1.000	.372	.032	-.047	.051	-.050
I10										1.000	.093	.283	.099	.350
I11											1.000	.069	.371	.225
I12												1.000	.069	-.032
I13													1.000	.294
I14														1.000

Table 4. PANEL 4: cumulative three-year data set: Correlation matrix

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14
I1	1.000	**.567**	.253	**.631**	**.519**	.067	.068	-.010	.109	-.143	-.037	-.168	.185	.134
I2		1.000	.341	**.607**	.372	.101	.172	-.365	.100	.112	.002	.076	.257	.088
I3			1.000	.263	.193	-.018	**-.458**	.119	-.037	.003	.037	-.013	.076	.060
I4				1.000	.337	-.073	.075	-.134	.146	-.072	.032	.013	.175	-.013
I5					1.000	.073	.165	.046	.304	**.473**	.153	-.033	.286	**.480**
I6						1.000	-.070	-.346	**.519**	.334	-.073	.023	-.150	-.018
I7							1.000	.035	.037	.060	.031	.022	.054	.106
I8								1.000	-.188	-.230	.039	-.125	-.046	.159
I9									1.000	**.445**	-.015	.042	-.082	-.020
I10										1.000	.058	.309	.070	.390
I11											1.000	.047	.179	.133
I12												1.000	.148	.089
I13													1.000	.159
I14														1.000

Table 5. PCA

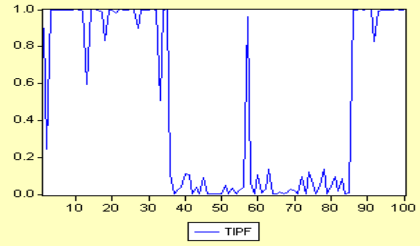
Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.294	23.529	23.529	3.294	23.529	23.529	2.795	19.963	19.963
2	2.079	14.847	38.377	2.079	14.847	38.377	1.987	14.191	34.154
3	1.660	11.858	50.235	1.660	11.858	50.235	1.797	12.834	46.988
4	1.563	11.163	61.398	1.563	11.163	61.398	1.613	11.524	58.512
5	1.124	8.026	69.424	1.124	8.026	69.424	1.284	9.169	67.681
6	1.011	7.224	76.648	1.011	7.224	76.648	1.255	8.966	**76.648**
7	.763	5.447	82.095						
8	.652	4.659	86.754						
9	.537	3.838	90.592						
10	.422	3.013	93.605						
11	.330	2.360	95.965						
12	.245	1.751	97.717						
13	.184	1.315	99.032						
14	.136	.968	100.000						

PANEL 1: first- year data set : The single-period logit model tests

Equation: UNTITLED Workfile: 100DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids



Forecast: TIPF
Actual: TIP
Forecast sample: 1 100
Included observations: 100

Root Mean Squared Error	0.146178
Mean Absolute Error	0.050230
Mean Abs. Percent Error	2.247152
Theil Inequality Coefficient	0.104612
Bias Proportion	0.001308
Variance Proportion	0.041494
Covariance Proportion	0.957198

Table 6.

Equation: LOGIT1 Workfile: 100DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/19/09 Time: 07:59
Sample: 1 70
Included observations: 70
Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	34	1	35	35	35	70
P(Dep=1)>C	1	34	35	0	0	0
Total	35	35	70	35	35	70
Correct	34	34	68	35	0	35
% Correct	97.14	97.14	97.14	100.00	0.00	50.00
% Incorrect	2.86	2.86	2.86	0.00	100.00	50.00
Total Gain*	-2.86	97.14	47.14			
Percent Ga...	NA	97.14	94.29			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	32.93	2.07	35.00	17.50	17.50	35.00
E(# of Dep=1)	2.07	32.93	35.00	17.50	17.50	35.00
Total	35.00	35.00	70.00	35.00	35.00	70.00
Correct	32.93	32.93	65.87	17.50	17.50	35.00
% Correct	94.10	94.10	94.10	50.00	50.00	50.00
% Incorrect	5.90	5.90	5.90	50.00	50.00	50.00
Total Gain*	44.10	44.10	44.10			
Percent Ga...	88.19	88.19	88.19			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

Table 7.

Equation: UNTITLED Workfile: 100DISTRESS\Untitled

iew | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 00:08
Sample: 1 70
Included observations: 70
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	1.E-15	0.0003	7	6.99971	0	0.00029	7	0.00029
2	0.0003	0.0049	7	6.98473	0	0.01527	7	0.01530
3	0.0096	0.0275	7	6.87082	0	0.12918	7	0.13160
4	0.0295	0.0622	7	6.70439	0	0.29561	7	0.30864
5	0.0919	0.2460	6	6.09048	1	0.90952	7	0.01035
6	0.5075	0.9812	1	1.32556	6	5.67444	7	0.09864
7	0.9895	1.0000	0	0.02425	7	6.97575	7	0.02433
8	1.0000	1.0000	0	4.4E-05	7	6.99996	7	4.4E-05
9	1.0000	1.0000	0	4.0E-09	7	7.00000	7	4.0E-09
10	1.0000	1.0000	0	4.4E-16	7	7.00000	7	0.00000
		Total	35	35.0000	35	35.0000	70	0.58919

H-L Statistic:	0.5892	Prob. Chi-Sq(8)	0.9998
Andrews Statistic:	26.0016	Prob. Chi-Sq(10)	0.0037

Table 8.

Equation: UNTITLED Workfile: 100DISTRESS\Untitled

iew | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Correlogram of Standardized Residuals

Date: 06/22/09 Time: 00:46
Sample: 1 70
Included observations: 64

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.101	0.101	0.6885	0.407
		2	0.031	0.021	0.7533	0.686
		3	0.057	0.053	0.9819	0.806
		4	0.048	0.037	1.1413	0.888
		5	0.042	0.032	1.2689	0.938
		6	0.105	0.095	2.0736	0.913
		7	-0.004	-0.029	2.0747	0.956
		8	-0.010	-0.016	2.0822	0.978
		9	0.018	0.009	2.1069	0.990
		10	-0.000	-0.010	2.1069	0.995
		11	0.064	0.062	2.4336	0.996
		12	0.072	0.053	2.8602	0.996
		13	0.006	-0.005	2.8627	0.998
		14	0.042	0.037	3.0089	0.999
		15	0.034	0.013	3.1061	1.000
		16	0.086	0.076	3.7613	0.999
		17	0.068	0.036	4.1784	0.999
		18	0.019	-0.008	4.2132	1.000
		19	0.038	0.030	4.3452	1.000
		20	0.023	-0.001	4.3975	1.000
		21	0.056	0.044	4.7060	1.000
		22	0.005	-0.025	4.7084	1.000

PANEL 2: second-year data set: The single-period logit model tests

Table 9.

Equation: UNTITLED Workfile: 2007\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 01:41
Sample: 1 70
Included observations: 70
Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	29	9	38	35	35	70
P(Dep=1)>C	6	26	32	0	0	0
Total	35	35	70	35	35	70
Correct	29	26	55	35	0	35
% Correct	82.86	74.29	78.57	100.00	0.00	50.00
% Incorrect	17.14	25.71	21.43	0.00	100.00	50.00
Total Gain*	-17.14	74.29	28.57			
Percent Ga...	NA	74.29	57.14			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	24.84	10.16	35.00	17.50	17.50	35.00
E(# of Dep=1)	10.16	24.84	35.00	17.50	17.50	35.00
Total	35.00	35.00	70.00	35.00	35.00	70.00
Correct	24.84	24.84	49.69	17.50	17.50	35.00
% Correct	70.98	70.98	70.98	50.00	50.00	50.00
% Incorrect	29.02	29.02	29.02	50.00	50.00	50.00
Total Gain*	20.98	20.98	20.98			
Percent Ga...	41.97	41.97	41.97			

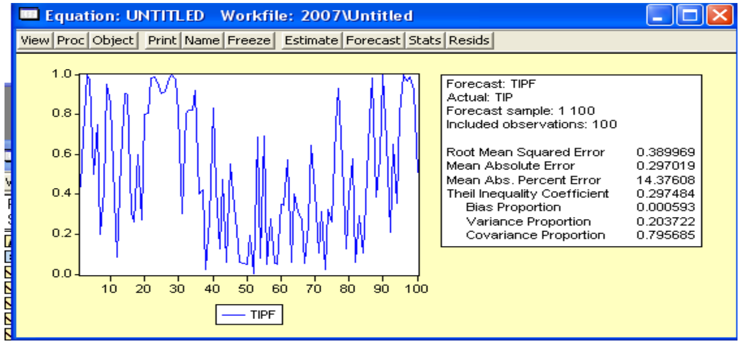


Table 10.

Equation: UNTITLED Workfile: 2007\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 01:41
Sample: 1 70
Included observations: 70
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0004	0.0536	7	6.72363	0	0.27637	7	0.28773
2	0.0554	0.1246	6	6.47454	1	0.52546	7	0.46334
3	0.1952	0.2737	4	5.32518	3	1.67482	7	1.37831
4	0.2788	0.3495	5	4.82357	2	2.17643	7	0.02075
5	0.3791	0.4215	5	4.15219	2	2.84781	7	0.42551
6	0.4313	0.5746	4	3.45834	3	3.54166	7	0.16768
7	0.5988	0.8027	3	2.13843	4	4.86157	7	0.49982
8	0.8050	0.8540	1	1.24383	6	5.75617	7	0.05813
9	0.9014	0.9532	0	0.55305	7	6.44695	7	0.60050
10	0.9690	0.9999	0	0.10725	7	6.89275	7	0.10892
		Total	35	35.0000	35	35.0000	70	4.01068

H-L Statistic:	4.0107	Prob. Chi-Sq(8)	0.8562
Andrews Statistic:	19.4617	Prob. Chi-Sq(10)	0.0348

PANEL 3: third- year data set: The single-period logit model tests

Table 11.

Equation: UNTITLED Workfile: 2006_DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 15:42
Sample: 1 70
Included observations: 70
Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	32	7	39	35	35	70
P(Dep=1)>C	3	28	31	0	0	0
Total	35	35	70	35	35	70
Correct	32	28	60	35	0	35
% Correct	91.43	80.00	85.71	100.00	0.00	50.00
% Incorrect	8.57	20.00	14.29	0.00	100.00	50.00
Total Gain*	-8.57	80.00	35.71			
Percent Ga...	NA	80.00	71.43			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	25.89	9.11	35.00	17.50	17.50	35.00
E(# of Dep=1)	9.11	25.89	35.00	17.50	17.50	35.00
Total	35.00	35.00	70.00	35.00	35.00	70.00
Correct	25.89	25.89	51.79	17.50	17.50	35.00
% Correct	73.98	73.98	73.98	50.00	50.00	50.00
% Incorrect	26.02	26.02	26.02	50.00	50.00	50.00
Total Gain*	23.98	23.98	23.98			
Percent Ga...	47.97	47.97	47.97			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation

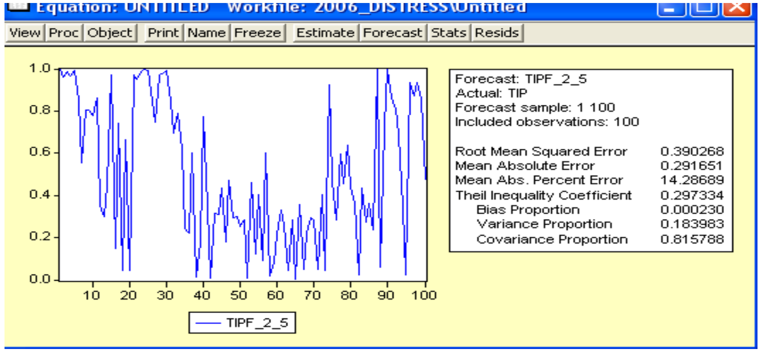


Table 12.

Equation: UNTITLED Workfile: 2006_DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 15:42
Sample: 1 70
Included observations: 70
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	2.E-07	0.0451	6	6.85911	1	0.14089	7	5.34633
2	0.0462	0.1779	5	6.28227	2	0.71773	7	2.55261
3	0.1794	0.2581	6	5.41052	1	1.58948	7	0.28284
4	0.2829	0.3020	6	4.96246	1	2.03754	7	0.74525
5	0.3119	0.4019	6	4.58387	1	2.41613	7	1.26751
6	0.4350	0.6001	5	3.43000	2	3.57000	7	1.40907
7	0.6171	0.7806	1	1.97965	6	5.02035	7	0.67596
8	0.7886	0.8596	0	1.20393	7	5.79607	7	1.45400
9	0.9513	0.9755	0	0.22898	7	6.77102	7	0.23673
10	0.9851	0.9995	0	0.05919	7	6.94081	7	0.05970
		Total	35	35.0000	35	35.0000	70	14.0300

H-L Statistic:	14.0300	Prob. Chi-Sq(8)	0.0810
Andrews Statistic:	30.0166	Prob. Chi-Sq(10)	0.0009

PANEL 3: third- year data set: Another valid single-period logit model that performed worse

Table 13.

Equation: EQ5_8_10 Workfile: UNTITLED\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 02:11
Sample: 1 70
Included observations: 70
Convergence achieved after 6 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	20.09805	6.877945	2.922101	0.0035
I5	-3.053198	0.793615	-3.847201	0.0001
I8	0.042224	0.016509	2.557654	0.0105
I10	1.051772	0.442094	2.379070	0.0174

Mean dependent var	0.500000	S.D. dependent var	0.503610
S.E. of regression	0.381071	Akaike info criterion	0.936818
Sum squared resid	9.584197	Schwarz criterion	1.065303
Log likelihood	-28.78863	Hannan-Quinn criter.	0.987854
Restr. log likelihood	-48.52030	Avg. log likelihood	-0.411266
LR statistic (3 df)	39.46334	McFadden R-squared	0.406668
Probability(LR stat)	1.38E-08		

Obs with Dep=0	35	Total obs	70
Obs with Dep=1	35		

Table 14.

Equation: EQ5_8_10 Workfile: UNTITLED\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 02:11
Sample: 1 70
Included observations: 70
Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	30	8	38	35	35	70
P(Dep=1)>C	5	27	32	0	0	0
Total	35	35	70	35	35	70
Correct	30	27	57	35	0	35
% Correct	85.71	77.14	81.43	100.00	0.00	50.00
% Incorrect	14.29	22.86	18.57	0.00	100.00	50.00
Total Gain*	-14.29	77.14	31.43			
Percent Ga...	NA	77.14	62.86			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	25.51	9.49	35.00	17.50	17.50	35.00
E(# of Dep=1)	9.49	25.51	35.00	17.50	17.50	35.00
Total	35.00	35.00	70.00	35.00	35.00	70.00
Correct	25.51	25.51	51.01	17.50	17.50	35.00
% Correct	72.87	72.87	72.87	50.00	50.00	50.00
% Incorrect	27.13	27.13	27.13	50.00	50.00	50.00
Total Gain*	22.87	22.87	22.87			
Percent Ga...	45.75	45.75	45.75			

Table 15.

Equation: EQ5_8_10 Workfile: 2006_DISTRESS\Untitled

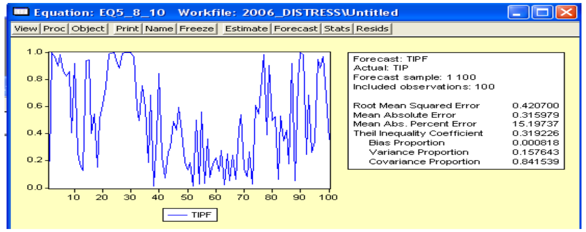
View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 02:11
Sample: 1 70
Included observations: 70
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0102	0.0611	7	6.78506	0	0.21494	7	0.22175
2	0.0732	0.1533	5	6.17211	2	0.82789	7	1.88205
3	0.1742	0.2196	5	5.67042	2	1.32958	7	0.41731
4	0.2291	0.2973	6	5.18298	1	1.81702	7	0.49616
5	0.3625	0.4304	5	4.18686	2	2.81314	7	0.39296
6	0.4919	0.5593	4	3.35979	3	3.64021	7	0.23459
7	0.5897	0.7549	2	2.41769	5	4.58231	7	0.11024
8	0.8239	0.9165	1	0.91404	6	6.08596	7	0.00930
9	0.9186	0.9859	0	0.29522	7	6.70478	7	0.30822
10	0.9948	0.9999	0	0.01582	7	6.98418	7	0.01586
		Total	35	35.0000	35	35.0000	70	4.08843

H-L Statistic:	4.0884	Prob. Chi-Sq(8)	0.8491
Andrews Statistic:	18.3299	Prob. Chi-Sq(10)	0.0496

	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	35	35	70	15	15	30
incorect	7	5	12	5	7	12
corect	28	30	58	10	8	18
% incorect	20,0	14,3	17,1	33,3	46,7	40,0
% corect	80,0	85,7	**82,9**	66,7	53,3	**60,0**



PANEL 4: cumulative three- year data set : hazard model with time invariant baseline hazard function

Table 16.

Equation: LOGIT_2_4 Workfile: 300DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/18/09 Time: 00:06
Sample: 1 210
Included observations: 210
Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	118	12	130	126	84	210
P(Dep=1)>C	8	72	80	0	0	0
Total	126	84	210	126	84	210
Correct	118	72	190	126	0	126
% Correct	93.65	85.71	90.48	100.00	0.00	60.00
% Incorrect	6.35	14.29	9.52	0.00	100.00	40.00
Total Gain*	-6.35	85.71	30.48			
Percent Ga...	NA	85.71	76.19			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	112.86	13.14	126.00	75.60	50.40	126.00
E(# of Dep=1)	13.14	70.86	84.00	50.40	33.60	84.00
Total	126.00	84.00	210.00	126.00	84.00	210.00
Correct	112.86	70.86	183.71	75.60	33.60	109.20
% Correct	89.57	84.35	87.48	60.00	40.00	52.00
% Incorrect	10.43	15.65	12.52	40.00	60.00	48.00
Total Gain*	29.57	44.35	35.48			
Percent Ga...	73.92	73.92	73.92			

Table 17.

Equation: LOGIT_2_4 Workfile: 300DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

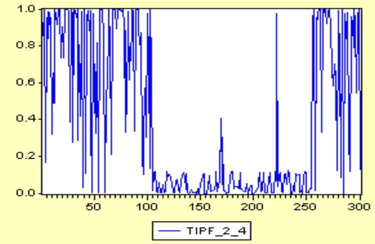
Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/18/09 Time: 00:06
Sample: 1 210
Included observations: 210
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	0.0003	21	20.9989	0	0.00109	21	0.00109
2	0.0004	0.0103	21	20.9074	0	0.09258	21	0.09299
3	0.0111	0.0320	21	20.5963	0	0.40365	21	0.41156
4	0.0330	0.0701	21	19.9903	0	1.00971	21	1.06071
5	0.0735	0.1141	21	18.9223	0	2.07768	21	2.30581
6	0.1166	0.4096	13	15.7525	8	5.24749	21	1.92475
7	0.4157	0.8389	4	6.99271	17	14.0073	21	1.92021
8	0.8542	0.9760	3	1.70991	18	19.2901	21	1.05963
9	0.9822	0.9995	1	0.12834	20	20.8717	21	5.95650
10	0.9997	1.0000	0	0.00124	21	20.9988	21	0.00124
		Total	126	126.000	84	84.0000	210	14.7345

H-L Statistic:	14.7345	Prob. Chi-Sq(8)	0.0645
Andrews Statistic:	90.2505	Prob. Chi-Sq(10)	0.0000

Equation: LOGIT_2_4 Workfile: 300DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids



Forecast: TIPF_2_4
Actual: TIP
Forecast sample: 1 300
Included observations: 300

Root Mean Squared Error	0.264255
Mean Absolute Error	0.131558
Mean Abs. Percent Error	5.641904
Theil Inequality Coefficient	0.218745
Bias Proportion	0.005018
Variance Proportion	0.057785
Covariance Proportion	0.937196

Table 18.

Equation: LOGIT_2_4 Workfile: 300DISTRESS\Untitled

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Correlogram of Standardized Residuals

Date: 06/22/09 Time: 17:07
Sample: 1 210
Included observations: 209

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.027	-0.027	0.1525	0.696
		2	0.088	0.087	1.8073	0.405
		3	0.132	0.138	5.5622	0.135
		4	0.074	0.077	6.7525	0.150
		5	-0.071	-0.092	7.8292	0.166
		6	0.073	0.036	8.9886	0.174
		7	0.127	0.131	12.516	0.085
		8	0.069	0.091	13.558	0.094
		9	0.030	0.009	13.757	0.131
		10	0.008	-0.059	13.770	0.184
		11	0.060	0.028	14.567	0.203
		12	0.005	0.023	14.573	0.266
		13	0.083	0.087	16.124	0.242
		14	-0.012	-0.042	16.158	0.304
		15	0.151	0.105	21.373	0.125
		16	-0.024	-0.032	21.505	0.160
		17	-0.011	-0.039	21.531	0.203
		18	0.091	0.075	23.442	0.174
		19	-0.026	-0.044	23.596	0.212
		20	-0.034	-0.040	23.867	0.248
		21	0.108	0.077	26.587	0.185

PANEL 4: cumulative three- year data set : hazard model with time varying baseline hazard function (exchange rate)

Table 19.

Equation: HAZARD2_4_CHANGE_EUR Workfile: 300DISTRESS\...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 18:07
Sample: 1 210
Included observations: 210
Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	117	9	126	126	84	210
P(Dep=1)>C	9	75	84	0	0	0
Total	126	84	210	126	84	210
Correct	117	75	192	126	0	126
% Correct	92.86	89.29	91.43	100.00	0.00	60.00
% Incorrect	7.14	10.71	8.57	0.00	100.00	40.00
Total Gain*	-7.14	89.29	31.43			
Percent Ga...	NA	89.29	78.57			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	114.05	11.95	126.00	75.60	50.40	126.00
E(# of Dep=1)	11.95	72.05	84.00	50.40	33.60	84.00
Total	126.00	84.00	210.00	126.00	84.00	210.00
Correct	114.05	72.05	186.10	75.60	33.60	109.20
% Correct	90.52	85.78	88.62	60.00	40.00	52.00
% Incorrect	9.48	14.22	11.38	40.00	60.00	48.00
Total Gain*	30.52	45.78	36.62			
Percent Ga...	76.29	76.29	76.29			

Table 20.

Equation: HAZARD2_4_CHANGE_EUR Workfile: 300DISTRESS\Untit...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 18:07
Sample: 1 210
Included observations: 210
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	9.E-05	21	20.9995	0	0.00048	21	0.00048
2	0.0001	0.0057	21	20.9583	0	0.04166	21	0.04174
3	0.0069	0.0177	21	20.7471	0	0.25289	21	0.25598
4	0.0178	0.0437	21	20.3723	0	0.62766	21	0.64700
5	0.0439	0.1379	21	19.5870	0	1.41302	21	1.51496
6	0.1432	0.4877	12	15.2598	9	5.74015	21	2.54765
7	0.5354	0.8267	6	6.60235	15	14.3977	21	0.08015
8	0.8403	0.9888	3	1.41294	18	19.5871	21	1.91124
9	0.9903	0.9999	0	0.06031	21	20.9397	21	0.06048
10	0.9999	1.0000	0	0.00027	21	20.9997	21	0.00027
		Total	126	126.000	84	84.0000	210	7.05994

H-L Statistic:	7.0599	Prob. Chi-Sq(8)	0.5302
Andrews Statistic:	94.8129	Prob. Chi-Sq(10)	0.0000

PANEL 4: cumulative three- year data set : another hazard model with time varying baseline hazard function (lending rate) that performed worse

	In sample			Out-of-sample		
	healthy	unhealthy	TOTAL	healthy	unhealthy	TOTAL
Total	105	105	210	45	45	90
incorect	7	7	14	2	7	9
corect	98	98	196	43	38	81
% incorect	6,7	6,7	6,7	4,4	15,6	10,0
% corect	93,3	93,3	**93,3**	95,6	84,4	**90,0**

Table 21.

Equation: HAZARD2_4_CHANGE_LENDIN Workfile: 300...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 18:04
Sample: 1 210
Included observations: 210
Convergence achieved after 8 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
CHANGE_LENDING	0.042989	0.018990	2.263813	0.0236
C	-1.760865	0.373128	-4.719193	0.0000
I2	-0.184381	0.059693	-3.088823	0.0020
I4	-0.000301	8.28E-05	-3.643115	0.0003

Mean dependent var	0.400000	S.D. dependent var	0.491069
S.E. of regression	0.242250	Akaike info criterion	0.424357
Sum squared resid	12.08911	Schwarz criterion	0.488112
Log likelihood	-40.55753	Hannan-Quinn criter.	0.450131
Restr. log likelihood	-141.3325	Avg. log likelihood	-0.193131
LR statistic (3 df)	201.5498	McFadden R-squared	0.713035
Probability(LR stat)	0.000000		

Obs with Dep=0	126	Total obs	210
Obs with Dep=1	84		

Table 22.

Equation: HAZARD2_4_CHANGE_LENDIN Workfile: 300...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 18:04
Sample: 1 210
Included observations: 210
Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	118	8	126	126	84	210
P(Dep=1)>C	8	76	84	0	0	0
Total	126	84	210	126	84	210
Correct	118	76	194	126	0	126
% Correct	93.65	90.48	92.38	100.00	0.00	60.00
% Incorrect	6.35	9.52	7.62	0.00	100.00	40.00
Total Gain*	-6.35	90.48	32.38			
Percent Ga...	NA	90.48	80.95			

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	113.87	12.13	126.00	75.60	50.40	126.00
E(# of Dep=1)	12.13	71.87	84.00	50.40	33.60	84.00
Total	126.00	84.00	210.00	126.00	84.00	210.00
Correct	113.87	71.87	185.74	75.60	33.60	109.20
% Correct	90.37	85.56	88.45	60.00	40.00	52.00
% Incorrect	9.63	14.44	11.55	40.00	60.00	48.00
Total Gain*	30.37	45.56	36.45			
Percent Ga...	75.94	75.94	75.94			

Table 23.

Equation: HAZARD2_4_CHANGE_LENDIN Workfile: 300DISTRESS\U...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: TIP
Method: ML - Binary Logit (Quadratic hill climbing)
Date: 06/22/09 Time: 18:04
Sample: 1 210
Included observations: 210
Andrews and Hosmer-Lemeshow Goodness-of-Fit Tests
Grouping based upon predicted risk (randomize ties)

	Quantile of Risk		Dep=0		Dep=1		Total	H-L
	Low	High	Actual	Expect	Actual	Expect	Obs	Value
1	0.0000	0.0002	21	20.9990	0	0.00095	21	0.00095
2	0.0002	0.0072	21	20.9439	0	0.05610	21	0.05625
3	0.0073	0.0198	21	20.7090	0	0.29098	21	0.29507
4	0.0203	0.0458	21	20.2688	0	0.73117	21	0.75754
5	0.0460	0.1170	21	19.1996	0	1.80035	21	1.96917
6	0.1260	0.4967	13	15.5773	8	5.42269	21	1.65138
7	0.5092	0.8487	5	6.72696	16	14.2730	21	0.65230
8	0.8533	0.9849	2	1.49200	19	19.5080	21	0.18619
9	0.9884	0.9998	1	0.08252	20	20.9175	21	10.2406
10	0.9998	1.0000	0	0.00075	21	20.9993	21	0.00075
		Total	126	126.000	84	84.0000	210	15.8102

H-L Statistic:	15.8102	Prob. Chi-Sq(8)	0.0452
Andrews Statistic:	85.7665	Prob. Chi-Sq(10)	0.0000

ANNEX ANN

```
function teste_retele_neurale
    fileDate = 'C:\\Users\\Desktop\\dizertatie-mada\\2008.csv';
    date = citesteDate(fileDate);
    classifyFF(date)

function readData = citesteDate(fileDate)
    fpath = char(fileDate);
    fid = fopen(fpath);
    C = textscan(fid,'%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f','delimiter',';');
    fclose(fid);
    readData = [C{1}, C{2}, C{3}, C{4}, C{5}, C{6}, C{7}, C{8}, C{9}, C{10}, C{11},
C{12}, C{13}, C{14}, C{15}];
    %readData = readData';

function classifyFF(date)
    inputRange = [];

    VMIN = -1;
    VMAX = 1;

    for col=2:length(date(1,:))
        vcolmin = min(date(:,col));
        vcolmax = max(date(:,col));
        for row=1:length(date(:,1))
            if (date(row,col) >= 0)
                date(row,col) = date(row,col) / vcolmax * VMAX;
            else
                date(row,col) = date(row,col) / vcolmin * VMIN;
            end
        end
        inputRange = [inputRange; VMIN, VMAX];
    end

   NUM_NEURONS = 1;
   NEURON_LAYERS = [NUM_NEURONS, 1];
   fcts = {'tansig', 'logsig'};

   net = newff(inputRange, NEURON_LAYERS, fcts, 'traingdx');
   net.trainParam.epochs = 2000;
   net.trainParam.show = 100;
   net.trainParam.goal = 1e-15;

   % create test inputs and outputs
   testInput = [];
   testOutput = [];

   numTestInputs = round(0.7 * length(date(:,1)))

   testInput = date(1:numTestInputs, 2:15);
   testOutput = date(1:numTestInputs, 1);

   %testInput
   %testOutput

   testInput = testInput';
   testOutput = testOutput';

   net = train(net, testInput, testOutput);

   net.IW{1};

   InSampleOutput = sim(net, testInput);

   % compute #OK
   InSampleOK = 0;
   for tinput=1:numTestInputs
       if (date(tinput, 1) < 0.5)
           correct = 0;
```

```
        else
            correct = 1;
        end

        if (InSampleOutput(tinput) < 0.5)
            output = 0;
        else
            output = 1;
        end

        if (correct == output)
            InSampleOK = InSampleOK + 1;
        end
    end

    InSampleOK
    numTestInputs
    InSampleOK/numTestInputs*100

    OutSampleInput = date(numTestInputs+1:length(date(:,1)), 2:15)';
    OutSampleCorrectOutput = date(numTestInputs+1:length(date(:,1)), 1);
    OutSampleOutput = sim(net, OutSampleInput);

    OutSampleOK = 0;
    for tinput=numTestInputs+1:length(date(:,1))
        if (date(tinput, 1) < 0.5)
            correct = 0;
        else
            correct = 1;
        end

        if (OutSampleOutput(tinput - numTestInputs) < 0.5)
            output = 0;
        else
            output = 1;
        end

        if (correct == output)
            OutSampleOK = OutSampleOK + 1;
        end
    end

    OutSampleOK
    length(date(:,1))-numTestInputs
    OutSampleOK/(length(date(:,1))-numTestInputs)*100

    %figure;
    %plot(1:numTestInputs,      date(1:numTestInputs,1),      'b',      1:numTestInputs,
InSampleOutput(1:numTestInputs), 'r');
    %title('In-Sample Results');
    %xlabel('Index');
    %ylabel('Value');
    %legend({'Correct Value', 'Estimated Value'});

    figure;
    plot(1:(length(date(:,1))-numTestInputs),
date(numTestInputs+1:length(date(:,1)),1),  'b',  1:(length(date(:,1))-numTestInputs),
OutSampleOutput(1:1:(length(date(:,1))-numTestInputs)), 'r');
    title('Out-Sample Results');
    xlabel('Index');
    ylabel('Value');
    legend({'Correct Value', 'Estimated Value'});
```

DATA BASE

	CODE	TYPE	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14
1	INSI 08	1	-5,9	-10,7	-26,2	-8228,9	11,9	1,7	139,5	57,2	14932,8	11,2	0,8	10,6	11,3	19,4
2	INSI 07	1	-6,5	-11,8	-20,6	-6193,4	11,5	2,1	71,1	40,7	11101,5	10,9	-68,7	11,2	17,8	19,3
3	INSI 06	1	-24,6	-41,8	-73,2	-17146,5	11,3	1,0	74,6	42,6	385,1	10,6	120,6	-21,3	-13,3	19,2
4	GRET 08	1	-1,0	-0,6	-1,4	-855,5	11,8	6,5	100,3	42,7	76954,2	11,9	-91,8	36,7	36,5	16,6
5	GRET 07	1	-16,5	-10,1	-18,6	-9388,2	11,0	1,3	75,2	40,9	9850,5	11,4	-27,8	19,6	117,4	16,3
6	GRET 06	1	-49,6	-16,8	23,4	-12186,8	10,4	0,3	-226,7	162,4	-60681,1	11,2	-97,3	-85,1	-88,6	16,2
7	HIJA 08	1	-18,7	-13,6	217,6	-4818,0	10,2	0,3	-246,2	104,9	-24886,2	10,5	-46,6	-5,0	1,8	17,3
8	HIJA 07	1	-35,7	-24,1	-222,5	-7121,5	10,0	0,4	113,3	91,7	-16711,6	10,3	15,5	-5,6	-20,6	17,4
9	HIJA 06	1	-24,5	-19,7	-64,5	-4998,2	9,9	0,5	227,4	69,4	-8166,4	10,1	23,4	35,7	-15,1	17,4
10	COFA 08	1	-12,8	-5,6	-9,2	-1075,6	9,1	0,6	65,9	39,8	-2815,8	9,9	-56,7	-2,6	-55,0	16,1
11	COFA 07	1	-13,3	-12,5	-19,5	-1974,4	9,7	0,7	55,8	35,8	-1797,4	9,7	17,8	-7,2	-25,4	16,2
12	COFA 06	1	-8,4	-9,8	-13,9	-1144,4	9,5	0,8	42,2	29,8	-825,7	9,4	-3,9	-9,1	-13,6	16,2
13	BANA 08	1	-25,6	-3,5	-6,9	-36786,9	11,9	0,9	96,8	49,1	-65186,4	13,9	-33,3	72,0	1,9	16,1
14	BANA 07	1	-39,1	-9,1	-9,6	-13423,0	10,7	7,5	5,6	5,3	51270,4	11,9	-55,1	-1,3	-69,8	15,5
15	BANA 06	1	-26,3	-20,0	-73,9	-3883,2	9,7	0,5	269,6	72,9	-7140,4	9,9	-24,5	-10,0	-23,8	15,5
16	ARIY 08	1	-55,9	-36,3	48,7	-54313,5	11,5	0,1	-234,0	174,6	-240548,7	11,9	9,6	-8,7	-13,3	17,1
17	ARIY 07	1	-44,2	-30,3	86,5	-39016,7	11,3	0,1	-386,0	135,0	-154243,5	11,8	49,6	-11,9	-17,5	17,2
18	ARIY 06	1	-24,4	-17,8	228,9	-23915,3	11,5	0,2	-257,1	104,9	-112137,6	11,8	144,6	-3,3	7,5	17,3
19	BIBU 08	1	-11,8	-0,5	-0,5	-9489,1	12,0	17,6	0,7	0,7	203084,6	14,4	-56,5	-0,6	-18,0	18,5
20	BIBU 07	1	-22,3	-1,2	-1,2	-13305,6	11,2	10,7	0,9	0,9	93995,6	13,9	35,5	-0,9	34,3	18,5
21	BIBU 06	1	-22,1	-0,9	-0,9	-9350,1	10,9	12,5	0,7	0,7	84220,9	13,9	44,4	50,1	41,6	18,5
22	CABU 08	1	-53,9	-2,8	-2,8	-22806,7	11,1	3,1	1,0	1,0	17453,0	13,6	-76,4	2,2	18,4	15,8
23	CABU 07	1	-171,2	-12,0	-12,2	-79226,8	10,8	9,2	1,1	1,1	35832,5	13,4	121,4	5,3	-28,7	15,8
24	CABU 06	1	-87,4	-5,7	-6,0	-23156,6	10,5	3,8	4,5	4,3	21767,6	12,9	-62,9	-3,8	-5,0	15,7
25	CARC 08	1	-15,4	-42,0	-149,0	-6897,5	10,7	1,0	252,9	71,4	582,9	9,7	-3,5	-23,5	-16,5	13,9
26	CARC 07	1	-13,3	-33,3	-62,0	-4766,9	10,4	1,6	85,9	46,2	4223,6	9,6	227,5	-31,1	-1,9	14,1
27	CARC 06	0	-4,0	-7,0	-11,7	-1215,0	10,6	2,0	66,2	39,7	7153,7	9,8	-115,1	-20,5	-0,5	14,5
28	CAST 08	1	-137,7	-11,6	-13,5	-21402,3	11,6	0,5	10,2	8,7	-7850,0	12,1	10,9	-26,7	-46,8	15,9
29	CAST 07	1	-66,0	-7,7	-10,8	-14560,8	10,2	0,3	33,2	23,7	-31512,1	12,2	339,5	215,8	-38,7	16,2
30	CAST 06	0	-5,5	-3,3	-17,1	-1496,5	10,4	0,6	327,6	62,7	-12546,1	10,7	-139,8	36,6	-2,1	15,0
31	CEDO 08	1	-18,3	-10,5	-16,5	-28373,7	12,1	0,5	55,6	35,5	-43144,3	12,5	-33,5	-21,2	-32,2	17,8
32	CEDO 07	1	-18,7	-12,5	-21,3	-16275,8	11,6	0,8	65,0	38,1	-7647,9	11,8	27,4	41,0	38,2	18,1
33	CEDO 06	1	-20,3	-13,8	-17,3	-9381,2	11,0	1,0	25,1	20,1	-384,0	11,1	110,4	7,6	-42,8	17,7
34	CEOF 08	1	-9,5	-14,0	-32,9	-22126,9	12,6	1,0	138,1	58,8	-4433,1	12,0	101,1	-16,9	70,0	18,1
35	CEOF 07	1	-1,5	-1,0	-2,2	-2894,5	12,3	1,1	80,9	37,9	5385,6	12,5	-51,4	180,3	69,9	18,3
36	CEOF 06	1	-5,1	-6,0	-14,2	-7951,3	12,0	0,8	140,1	59,6	-18972,6	11,8	158,4	21,8	25,4	17,3
37	CHEM 08	1	-3,2	-1,8	-2,1	-4363,7	11,9	2,2	19,1	16,1	25910,5	12,4	-78,2	66,8	65,2	18,0
38	CHEM 07	0	-24,6	-13,8	-17,6	-13339,5	10,9	5,0	27,9	21,8	25426,9	11,5	-304,8	4,0	-31,4	17,5
39	CHEM 06	0	4,2	3,5	3,7	2996,2	11,2	11,7	4,7	4,5	40543,2	11,3	-202,6	2,9	9,4	17,5
40	CIMD 08	1	-16,8	-32,4	44,5	-11227,1	11,3	1,6	-236,6	172,0	11964,0	10,5	40,8	-26,7	13,9	15,3
41	CIMD 07	0	-13,6	-16,8	55,2	-6859,5	11,0	1,2	-267,6	130,5	5316,5	10,6	-240,0	-20,2	1,9	15,6
42	CIMD 06	0	0,6	0,6	74,5	275,1	11,0	1,5	248,5	116,6	15020,2	10,8	-80,7	43,2	12,4	15,8
43	CIDT 08	1	-64,5	-11,9	-13,1	-9823,6	10,2	5,0	10,2	9,2	30371,9	11,3	-36,6	-9,9	55,9	15,1

44	CIDT 07	1	-158,8	-16,9	-18,2	-12580,8	9,8	6,7	8,2	7,6	31840,9	11,2	24,9	-14,4	-44,5	15,2
45	CIDT 06	0	-70,5	-11,5	-12,4	-7118,7	9,6	6,7	7,3	6,8	23399,3	11,0	-142,4	-21,9	-35,1	15,3
46	COTA 08	1	-19,0	-1,9	-2,5	-22273,9	11,7	1,5	32,8	24,7	39483,8	14,0	309,2	3,4	38,5	18,2
47	COTA 07	0	-6,4	-0,5	-0,6	-4921,2	11,3	6,9	25,3	20,2	157079,1	13,8	-132,9	551,0	-11,7	18,1
48	COTA 06	0	17,3	9,4	14,1	12393,3	11,2	0,6	48,9	32,9	-7577,8	11,8	69,5	45,0	10,8	16,3
49	COTM 08	1	-9,5	-1,8	-2,0	-17708,6	12,2	6,4	9,7	8,8	410639,8	13,8	79,6	74,4	34,3	17,1
50	COTM 07	1	-7,1	-1,8	-1,9	-4601,9	11,1	4,7	3,9	3,8	36034,1	12,5	-35,3	81,1	32,2	16,6
51	COTM 06	0	-14,5	-5,0	-5,5	-6013,7	10,7	4,3	9,1	8,2	32612,0	11,7	-279,5	-4,5	-12,6	16,0
52	CFOR 08	1	-5,0	-2,7	-2,9	-2577,3	11,0	6,9	5,7	5,3	29939,4	11,5	-63,5	-1,2	192,8	16,1
53	CFOR 07	0	-40,5	-7,4	-7,8	-7515,3	10,5	7,7	4,7	4,5	30642,2	11,5	-134,4	-3,3	-17,2	16,1
54	CFOR 06	0	97,6	20,7	21,4	15178,3	11,0	20,7	2,1	2,0	29300,6	11,2	-189,7	-2,1	-67,6	16,1
55	RCHI 08	1	-44,0	-8,0	-9,6	-67235,6	11,9	1,3	20,2	16,8	17703,0	13,6	-18,4	102,7	11,5	19,5
56	RCHI 07	1	-60,2	-19,8	-29,2	-77972,2	11,8	3,2	46,2	31,3	25407,4	12,9	56,4	-21,5	20,9	18,8
57	RCHI 06	1	-46,5	-9,9	-14,5	-42121,8	11,4	2,4	43,7	30,0	14569,5	13,0	250,9	-3,5	5,7	19,0
58	ELNV 08	1	-23,5	-10,7	-166,7	-19427,7	11,4	0,4	246,1	94,0	-55050,3	12,1	112,4	25,4	35,9	17,2
59	ELNV 07	0	-15,0	-6,3	-39,1	-8977,3	11,6	0,7	218,0	83,8	-13008,8	11,9	-152,4	44,5	21,9	17,0
60	ELNV 06	0	34,9	17,4	53,6	18020,7	11,3	0,5	207,7	67,5	-24886,9	11,5	-284,0	3,7	-2,1	16,6
61	EXPV 08	1	-8,6	-7,1	-15,5	-3316,9	10,6	1,1	118,1	53,9	685,3	10,8	32,0	57,3	52,3	15,7
62	EXPV 07	1	-9,9	-8,5	-11,0	-3056,3	10,3	0,7	29,8	22,9	-2667,0	10,5	-51,0	-4,3	14,7	15,3
63	EXPV 06	1	-23,2	-16,5	-20,3	-5346,6	10,1	0,8	22,5	18,3	-1021,5	10,4	37,0	-6,7	-21,3	15,3
64	FORO 08	1	-276,8	-83,0	-115,8	-11015,3	7,6	0,4	39,6	28,3	-2295,6	9,5	184,3	-45,8	-26,3	13,1
65	FORO 07	1	-87,7	-9,3	-10,2	-6648,8	8,9	5,3	10,2	9,3	28251,4	11,2	207,6	53,1	10,0	13,7
66	FORO 06	0	-15,9	-2,3	-2,8	-836,8	9,0	5,4	19,8	16,5	26056,9	10,5	-103,9	-18,1	-7,0	13,3
67	FRTI 08	1	-54,3	-12,2	-230,1	-22075,0	10,8	0,1	245,1	94,1	-147069,5	12,1	-31,7	3,9	-6,1	19,5
68	FRTI 07	1	-74,7	-18,6	-112,4	-31161,6	10,8	0,1	488,9	80,8	-121743,0	12,0	36,4	100,6	64,2	19,5
69	FRTI 06	1	-89,9	-27,3	89,8	-21403,0	10,5	0,1	-408,1	124,0	-86403,6	11,3	-23,0	-9,0	31,9	18,8
70	GIUR 08	1	-31,7	-37,0	43,5	-19605,6	11,2	0,2	-211,9	180,6	-79508,3	10,9	166,7	3,5	-3,5	16,8
71	GIUR 07	1	-11,5	-14,4	29,8	-5909,3	11,1	0,2	-294,0	141,9	-45782,9	10,6	-51,4	64,1	26,9	16,8
72	GIUR 06	1	-30,0	-48,5	47,8	-9301,0	10,4	0,1	-183,2	186,0	-30690,5	9,9	15,1	12,4	-10,0	16,3
73	GRIU 08	1	-154,6	-45,5	-56,7	-58192,4	10,3	2,3	24,0	19,2	31977,5	11,8	0,0	0,0	0,0	14,1
74	GRIU 07	1	-154,6	-45,5	-56,7	-58192,4	10,3	2,3	24,0	19,2	31977,5	11,8	13,4	-33,4	-16,1	14,1
75	GRIU 06	1	-188,2	-26,7	-31,9	-46638,5	10,2	3,7	19,1	16,0	75447,0	12,1	-0,7	-18,9	35,7	14,5
76	HIRY 08	1	-32,5	-5,8	-12,2	-18276,9	11,1	1,2	107,2	51,1	4106,9	12,7	-27,3	47,5	20,5	18,6
77	HIRY 07	1	-53,9	-11,8	-32,5	-20499,2	10,7	0,3	168,6	61,3	-44588,4	12,1	44,1	-0,7	-16,5	18,2
78	HIRY 06	1	-31,2	-8,1	-14,2	-10240,4	10,5	1,1	70,9	40,8	1918,4	11,7	-12,5	-0,7	3,6	18,2
79	IAME 08	1	-6,0	-1,9	-8,0	-3105,2	11,1	0,3	394,8	138,0	-125312,8	12,0	-71,5	-8,3	6,8	16,6
80	IAME 07	1	-22,4	-6,0	-26,1	-9884,0	11,0	0,3	364,7	129,8	-120682,2	12,0	92,0	-18,7	12,1	16,7
81	IAME 06	1	-13,1	-2,5	-12,0	-4165,9	10,4	0,5	289,0	103,7	-71789,5	12,0	-87,8	-5,1	-52,1	16,9
82	IASO 08	1	-37,9	-22,7	55,6	-8555,4	10,6	0,6	-217,8	129,8	-16407,1	10,5	309,8	114,8	5,1	15,8
83	IASO 07	1	-9,7	-11,9	15,2	-1741,4	10,1	0,9	-227,6	178,9	-1960,6	9,6	-35,3	-5,4	-16,3	15,1
84	IASO 06	0	-12,6	-17,4	27,6	-2244,4	10,1	0,8	-259,3	163,5	-3031,0	9,5	-149,8	-10,9	-13,3	15,1
85	CHIJ 08	1	-46,5	-8,0	-15,6	-7370,6	9,7	0,2	94,9	48,8	-35602,4	11,4	-70,6	-7,1	-23,7	13,0
86	CHIJ 07	1	-120,6	-25,2	-45,8	-25049,8	9,9	0,2	81,4	44,9	-37810,2	11,5	-38,1	-94,8	135,1	13,1
87	CHIJ 06	1	-258,4	-2,1	-2,2	-22486,7	8,5	0,2	2,3	2,2	-17845,1	13,9	9,8	1061,4	-17,1	16,1
88	MCTT 08	1	-33,0	-0,1	-0,1	-4154,8	9,4	0,1	1,7	1,7	-73776,7	15,3	-87,2	193,4	-52,1	17,9

89	MCTT 07	1	-123,9	-2,1	-2,1	-28235,5	9,9	0,1	2,3	2,2	-26076,6	14,1	-38,3	222,7	324,6	16,8
90	MCTT 06	1	-352,6	-10,9	-11,1	-42890,6	8,8	1,7	1,4	1,4	3787,9	12,9	181,3	-9,9	2,6	15,7
91	MRFT 08	1	-81,3	-28,2	51,5	-16601,1	10,0	0,2	-282,9	154,7	-69736,1	11,0	92,0	-24,2	-40,2	17,0
92	MRFT 07	1	-25,3	-11,1	216,8	-7814,4	10,5	0,3	-195,1	100,1	-51150,7	11,2	14,9	-19,3	9,7	17,3
93	MRFT 06	1	-24,2	-7,8	-41,8	-7071,5	10,5	0,3	234,2	81,3	-50883,4	11,4	-24,0	-16,8	-13,3	17,5
94	MOCR 08	1	-23,4	-12,9	-16,5	-6078,8	10,2	2,1	26,6	20,8	10853,9	10,8	235,2	-13,6	-29,9	16,1
95	MOCR 07	0	-2,6	-1,8	-2,2	-662,6	10,2	2,3	25,3	20,1	10137,0	10,5	-274,0	-0,1	-32,7	16,3
96	MOCR 06	0	1,0	1,0	1,2	281,5	10,2	2,5	22,7	18,4	7261,3	10,2	-69,3	-4,3	-2,5	16,3
97	MOBT 08	1	-2,7	-3,8	-5,3	-1214,4	10,7	0,8	39,4	28,1	-1929,1	10,4	-60,8	-3,9	3,5	16,5
98	MOBT 07	1	-7,2	-9,2	-14,0	-2601,3	10,5	0,8	51,6	33,9	-2006,4	10,2	84,7	-4,1	3,4	16,5
99	MOBT 06	1	-4,0	-4,8	-6,7	-1228,2	10,5	1,1	38,5	27,7	1017,3	10,2	-60,5	-15,9	-3,0	16,6
100	NUCA 08	1	-23,2	-11,8	-23,6	-12456,1	11,0	0,4	99,8	50,0	-30325,3	11,6	68,8	-4,1	34,0	15,5
101	NUCA 07	1	-18,4	-6,7	-11,3	-6209,7	10,6	0,6	69,1	41,0	-14148,1	11,4	276,4	25,2	-39,3	15,6
102	NUCA 06	0	-0,4	-0,3	-0,6	-157,0	10,6	0,4	89,0	47,2	-11227,8	10,9	-167,0	7,2	-31,2	15,4
103	ORTU 08	1	-264,8	-12,8	-15,9	-31297,5	10,6	1,0	23,9	19,3	-12070,4	14,7	261,3	-14,1	-98,0	16,7
104	ORTU 07	0	-14,3	-3,0	-20,1	-7676,1	10,9	0,8	559,9	84,8	-34034,9	12,4	-221,8	138,7	-25,7	16,8
105	ORTU 06	0	8,7	6,0	13,7	5296,5	11,1	0,4	125,6	54,7	-20253,8	11,4	-116,2	1,7	0,0	15,9
106	ACIS 08	0	0,4	0,5	1,0	333,6	11,4	1,0	87,4	46,5	218,2	11,1	233,6	29,1	40,4	16,2
107	ACIS 07	0	0,2	0,2	0,3	113,4	11,2	1,3	46,2	31,4	3703,9	11,0	-93,7	98,6	52,6	15,9
108	ACIS 06	0	4,6	6,3	9,5	2565,9	11,2	1,3	51,2	33,9	4321,2	10,6	-44,5	19,1	35,5	15,2
109	ADMY 08	0	13,4	5,6	5,8	6760,5	10,8	11,2	2,6	2,5	30938,8	11,7	-44,9	5,8	-3,8	16,0
110	ADMY 07	0	23,4	10,8	11,4	9681,8	10,7	4,6	4,8	4,5	14433,9	11,4	377,2	-1,1	8,1	16,0
111	ADMY 06	0	5,3	2,2	2,7	1768,4	10,4	1,1	17,3	14,4	717,8	11,3	-232,2	-3,5	14,6	16,0
112	BETA 08	0	2,6	3,9	17,2	22498,5	13,7	1,1	341,6	76,6	27093,4	13,3	67,6	37,3	36,3	19,8
113	BETA 07	0	2,1	3,2	13,4	13603,2	13,4	2,9	320,9	75,6	215228,2	13,0	-27,1	-12,7	-27,5	19,5
114	BETA 06	0	2,1	3,8	21,2	17547,4	13,6	2,8	438,8	78,6	242274,8	13,0	128,7	31,5	52,0	19,6
115	PERI 08	0	2,1	3,3	5,0	1942,9	11,6	1,5	51,5	34,0	10077,4	11,0	-81,0	16,6	17,0	14,1
116	PERI 07	0	12,7	20,1	27,5	7252,4	11,2	1,9	36,8	26,9	8854,7	10,5	101,1	9,5	28,8	13,9
117	PERI 06	0	8,1	11,0	18,9	3725,9	10,9	1,1	72,3	42,0	1343,8	10,4	116,9	-6,4	-0,2	13,8
118	ARTD 08	0	0,4	0,2	0,3	83,9	10,0	5,4	10,2	9,2	14865,4	10,5	-85,9	-7,0	1,3	12,5
119	ARTD 07	0	3,0	1,5	1,8	462,4	10,0	3,5	18,7	15,8	11970,7	10,3	6,4	-2,8	3,2	12,5
120	ARTD 06	0	2,9	1,4	1,7	488,8	9,9	2,0	24,4	19,6	7073,8	10,5	-122,2	3,1	-29,9	12,6
121	APAR08	0	0,5	0,8	1,3	332,8	11,2	1,2	77,3	45,4	3103,4	10,7	-47,8	11,1	-15,1	15,5
122	APAR 07	0	0,9	1,7	2,5	587,7	11,2	1,4	53,3	35,1	4404,7	10,5	-33,8	69,8	13,9	15,4
123	APAR 06	0	1,5	4,3	7,4	785,4	11,0	1,6	74,2	42,7	3979,0	9,8	60,2	-4,8	1,9	14,9
124	ATRD 08	0	9,7	21,5	31,8	18624,2	12,2	2,5	45,6	30,9	41172,5	11,4	59,9	8,5	30,2	18,2
125	ATRD 07	0	7,9	14,6	25,4	10678,8	11,9	2,0	70,3	40,5	29164,1	11,2	-31,7	14,4	-3,7	18,1
126	ATRD 06	0	11,1	24,5	42,4	14642,2	11,8	1,9	69,0	39,8	22438,9	11,0	386,5	32,9	142,7	17,9
127	ATLK 08	0	2,1	2,0	2,3	1070,3	10,9	2,3	17,0	14,5	6962,2	10,9	0,9	-0,7	-6,8	17,1
128	ATLK 07	0	1,9	2,0	2,4	916,4	10,8	1,6	20,9	17,4	4066,0	10,7	-68,4	0,2	-9,5	17,1
129	ATLK 06	0	5,6	6,3	7,7	2691,7	10,9	1,9	23,3	19,0	6732,5	10,7	104,8	12,7	-0,7	17,1
130	AUCS 08	0	19,1	1,0	1,0	24921,3	11,8	10,5	0,3	0,3	79936,9	14,8	21,5	269,9	-7,3	19,0
131	AUCS 07	0	14,6	3,0	3,0	19680,2	11,8	10,3	1,1	1,1	65158,5	13,4	337,8	10,8	76,1	17,7
132	AUCS 06	0	3,1	0,4	0,4	2257,5	11,5	5,6	2,0	2,0	40341,2	13,3	-38,8	-0,4	-4,1	17,6
133	AZOA 08	0	0,8	0,3	1,3	880,3	11,9	0,8	288,7	72,3	-23334,1	12,5	233,5	185,7	163,6	17,1

134	AZOA 07	0	0,6	0,3	0,4	277,3	10,9	1,2	42,8	30,2	3979,5	11,5	-64,0	8,2	-2,6	16,1
135	AZOA 06	0	1,6	0,9	1,3	856,6	11,0	2,0	51,5	34,4	19235,6	11,5	-265,4	17,8	-2,2	16,0
136	BARU 08	0	5,5	1,2	2,7	6271,5	11,9	1,6	122,7	55,1	54409,0	13,2	352,1	13,6	12,7	17,6
137	BARU 07	0	0,6	0,1	0,3	546,4	11,5	2,2	101,6	50,5	80156,9	12,9	-95,8	20,4	16,6	17,5
138	BARU 06	0	16,5	3,8	6,5	12322,2	11,6	1,3	73,6	42,5	27913,0	12,7	156,1	41,1	-16,3	17,3
139	BATV 08	0	33,6	15,9	16,8	31719,6	11,5	6,1	5,6	5,3	40310,3	12,2	111,2	13,8	63,7	17,5
140	BATV 07	0	26,0	8,6	9,1	15965,0	11,2	3,7	6,6	6,2	20427,1	12,1	205,5	5,3	45,2	17,4
141	BATV 06	0	12,4	3,0	3,2	5225,2	10,7	1,7	7,9	7,3	9172,0	12,1	44,6	-0,8	7,2	17,3
142	BATT 08	0	8,8	2,6	2,9	24073,0	12,6	4,9	8,9	8,1	289969,3	13,7	22,6	-3,4	-29,4	14,8
143	BATT 07	0	5,1	2,1	2,4	8417,1	12,0	3,6	16,1	13,9	144227,6	12,9	-25,5	3,7	85,6	14,9
144	BATT 06	0	12,7	2,9	3,3	9887,0	11,3	3,4	15,1	13,2	106479,1	12,7	-33,5	4,2	-25,0	14,8
145	CAOR 08	0	24,1	3,1	3,2	21708,0	11,6	33,9	2,1	2,0	469547,5	13,5	-41,1	206,2	17,6	18,0
146	CAOR 07	0	48,1	15,9	18,4	36419,5	11,8	7,3	4,4	3,8	54866,2	12,3	393,6	39,3	20,5	16,8
147	CAOR 06	0	7,3	2,8	3,3	4641,4	11,3	2,4	4,5	3,8	9232,8	12,0	-11,4	3,9	11,3	16,5
148	CEPO 08	0	9,4	5,5	6,9	9115,6	11,7	3,9	12,0	9,4	46304,7	12,0	-86,0	-22,6	-22,0	16,8
149	CEPO 07	0	52,3	30,2	41,5	41418,0	11,8	3,0	25,2	18,4	47675,0	11,8	240,0	90,2	-16,6	17,1
150	CEPO 06	0	1,7	2,3	3,8	1674,9	11,5	1,1	51,6	31,2	2470,2	11,2	216,3	4,5	10,4	16,4
151	CCOM 08	0	1,7	0,8	1,1	2162,1	11,8	1,4	33,3	25,0	23267,9	12,5	151,8	26,2	20,9	18,5
152	CCOM 07	0	0,8	0,4	0,5	846,2	11,6	1,5	33,6	25,2	24821,3	12,3	71,9	3,9	-9,9	18,3
153	CCOM 06	0	0,4	0,2	0,3	460,2	11,6	1,5	29,1	22,7	20756,6	12,2	-17,2	-1,1	11,4	18,3
154	CHIB 08	0	48,6	4,5	4,7	89367,5	14,4	9,1	3,3	3,2	1885535,0	16,8	188,3	7,2	19,2	16,8
155	CHIB 07	0	20,1	1,7	1,7	31003,3	14,3	16,3	2,0	1,9	2581561,0	16,7	-60,0	223,0	-0,7	16,7
156	CHIB 06	0	50,0	13,4	14,3	25854,6	13,2	12,1	7,0	6,6	710156,0	14,5	-16,3	-5,0	-24,0	15,6
157	CICA 08	0	2,4	4,5	8,6	2156,2	11,3	1,3	91,3	47,7	6037,9	10,8	356,7	19,4	47,2	16,7
158	CICA 07	0	0,8	1,2	2,3	459,6	10,9	1,1	99,5	49,9	2574,9	10,6	8,1	22,7	23,7	16,5
159	CICA 06	0	0,9	1,3	2,6	510,4	10,9	1,3	98,2	49,5	4029,3	10,6	8,8	29,4	31,0	16,3
160	CORE 08	0	5,3	1,3	1,3	9589,2	12,1	5,6	3,4	3,3	43001,5	13,5	106,1	811,3	34,2	16,6
161	CORE 07	0	3,5	5,8	6,3	4450,7	11,8	6,2	9,9	9,0	36246,6	11,3	0,1	7,9	-1,4	14,4
162	CORE 06	0	3,4	6,2	6,7	4092,2	11,7	4,4	9,0	8,3	18774,0	11,1	-56,2	5,2	-2,8	14,3
163	ELGS 08	0	2,8	8,1	25,6	2339,7	11,3	1,2	215,5	67,8	2815,0	10,3	97,3	1,8	8,1	17,0
164	ELGS 07	0	1,5	4,2	17,5	1044,6	11,2	1,1	319,1	75,5	1009,7	10,1	108,7	-18,3	-10,8	17,0
165	ELGS 06	0	0,1	0,3	1,8	80,0	11,2	1,0	324,2	83,6	-532,0	10,2	254,0	-20,1	-33,2	17,2
166	ELNG 08	0	2,1	2,9	4,8	7131,5	12,7	1,6	66,5	40,5	54437,5	12,4	164,1	7,2	26,7	18,7
167	ELNG 07	0	1,0	1,2	2,0	2781,0	12,5	1,5	68,0	40,4	42098,3	12,4	18,5	9,2	2,3	18,7
168	ELNG 06	0	0,9	1,1	1,8	2346,7	12,5	1,4	62,9	38,4	33203,7	12,3	214,4	21,5	6,7	18,6
169	CHAR 08	0	-7,5	-3,4	-3,5	-3471,0	10,8	11,4	4,0	3,9	41862,9	11,5	-257,1	1,2	-12,1	14,6
170	CHAR 07	0	4,2	2,2	2,2	2320,1	11,0	17,5	2,3	2,3	40057,5	11,6	-192,0	-3,1	3,9	14,6
171	CHAR 06	0	-4,8	-2,3	-2,4	-2520,5	10,9	4,4	7,9	7,4	27954,6	11,6	-207,4	41,2	10,0	14,6
172	CCRL 08	0	1,4	1,4	8,1	7093,3	13,1	1,1	467,0	81,8	34693,4	13,1	3,8	26,4	20,4	18,7
173	CCRL 07	0	1,6	1,7	6,4	6603,0	12,9	1,2	263,6	70,8	39121,6	12,9	-80,1	22,8	36,5	18,4
174	CCRL 06	0	11,2	10,6	30,9	32914,4	12,6	1,3	185,4	63,9	48062,6	12,6	212,6	55,7	5,2	18,2
175	REFE 08	0	8,1	9,2	14,1	14945,2	12,3	1,7	48,2	31,4	31046,2	12,0	0,0	0,0	0,0	18,8
176	REFE 07	0	8,1	9,2	14,1	14945,2	12,3	1,7	48,2	31,4	31046,2	12,0	35,8	48,8	106,3	18,8
177	REFE 06	0	12,3	10,1	16,2	13864,1	11,7	2,0	58,3	36,2	33512,3	11,8	95,3	187,7	66,1	18,4
178	GRLA 08	0	0,5	0,7	2,0	846,9	12,0	1,3	206,4	69,3	19528,3	11,7	219,3	-0,6	1,2	14,0

179	GRLA 07	0	0,1	0,1	0,4	135,9	11,9	1,5	205,9	67,3	34653,2	11,6	-25,5	4,5	-12,6	14,0
180	GRLA 06	0	0,1	0,2	0,5	168,4	11,8	1,4	193,8	66,0	23808,5	11,4	-97,1	4,8	-15,9	14,0
181	HEBE 08	0	4,2	6,0	6,5	2450,3	11,0	4,3	8,4	7,8	10573,7	10,6	23,0	0,8	0,6	15,0
182	HEBE 07	0	3,4	4,9	5,7	2065,5	11,0	2,5	14,9	13,0	8209,7	10,6	10,6	14,2	2,1	15,0
183	HEBE 06	0	3,2	5,1	5,4	1759,4	10,9	3,7	6,9	6,5	6051,5	10,5	21,6	3,4	15,7	14,9
184	IAIC 08	0	2,7	5,8	8,8	1589,5	11,1	1,6	49,9	33,2	5600,1	10,2	1,7	10,6	-0,1	15,5
185	IAIC 07	0	2,6	6,3	10,0	1405,7	10,9	1,6	54,7	34,7	4113,3	10,0	-18,9	5,0	6,4	15,4
186	IAIC 06	0	3,5	8,2	13,0	1807,4	10,9	1,5	58,6	37,0	3932,1	10,0	111,5	14,9	29,2	15,3
187	COBS 08	0	0,1	0,3	0,8	334,9	12,6	1,7	222,3	69,0	40431,1	11,8	-91,7	7,1	-18,8	18,3
188	COBS 07	0	1,1	3,3	9,9	4070,3	12,8	1,4	203,4	67,0	28058,4	11,7	0,0	0,0	0,0	18,2
189	COBS 06	0	1,1	3,3	9,9	4070,3	12,8	1,4	203,4	67,0	28058,4	11,7	2979,6	97,3	101,6	18,2
190	IAMU 08	0	7,8	8,3	10,3	4045,2	11,0	5,4	23,2	18,7	14518,0	10,8	3,3	20,5	-4,8	17,1
191	IAMU 07	0	7,2	9,7	11,5	3619,1	10,9	3,6	16,8	14,2	9905,5	10,5	25,0	11,5	13,6	17,0
192	IAMU 06	0	6,6	8,6	10,0	3114,9	10,7	3,3	13,7	11,9	9892,2	10,5	26,2	4,5	30,5	16,9
193	ICSH 08	0	5,8	4,8	8,2	6556,6	11,9	1,1	69,9	40,9	6673,0	11,8	204,4	17,1	53,3	17,7
194	ICSH 07	0	2,9	1,8	2,7	2165,7	11,4	1,2	49,2	33,0	5484,5	11,7	-97,3	50,6	40,6	17,6
195	ICSH 06	0	149,6	101,8	151,1	69562,6	11,8	2,7	48,4	32,6	29061,4	11,1	-338,0	1,2	51,9	17,2
196	INCT 08	0	4,0	3,9	4,9	3606,6	11,4	1,9	25,4	20,2	16302,9	11,4	42,2	10,0	21,4	15,6
197	INCT 07	0	3,4	3,0	3,5	2499,8	11,2	2,4	17,7	15,0	16758,0	11,3	-2,0	2,6	15,8	15,6
198	INCT 06	0	4,0	3,1	3,7	2410,1	11,0	2,4	16,9	14,4	15919,1	11,3	26,7	10,8	36,0	15,5
199	COMU 08	0	23,7	20,7	22,7	36439,4	11,9	4,0	8,1	7,3	38193,2	12,1	20,0	-9,4	2,7	14,4
200	COMU 07	0	20,3	15,6	17,9	30357,8	11,9	2,5	14,2	12,4	36987,4	12,2	52,5	10,8	-1,1	14,5
201	COMU 06	0	13,2	11,4	14,5	19907,8	11,9	1,6	26,9	21,1	23162,4	12,1	188,2	6,0	-8,4	14,4
202	INMP 08	0	4,3	8,2	26,4	4649,2	11,7	1,6	225,5	69,7	13260,7	10,9	47,4	14,5	-30,8	15,7
203	INMP 07	0	2,0	6,3	29,3	3181,6	12,0	0,8	348,3	75,5	-6557,8	10,8	97,0	76,5	130,0	15,5
204	INMP 06	0	2,3	5,7	21,0	1774,8	11,3	1,0	271,9	73,6	165,7	10,3	-23,2	91,7	47,8	15,0
205	JIUL 08	0	2,7	2,0	2,8	1609,6	11,0	1,6	40,6	28,9	2333,0	11,3	324,6	-6,4	15,1	15,9
206	JIUL 07	0	0,5	0,3	0,5	252,7	10,8	0,3	54,5	35,3	-5109,3	11,3	-96,2	-4,7	-3,8	16,0
207	JIUL 06	0	12,7	7,5	10,3	6200,4	10,8	1,1	37,2	27,1	368,7	11,3	21,2	12,1	32,5	16,0
208	CONC 08	0	3,3	6,8	12,8	4604,6	11,9	1,1	42,8	22,7	1837,4	11,1	232,2	7,5	141,8	15,3
209	CONC 07	0	0,3	0,3	0,6	239,4	11,3	1,3	82,0	39,4	7831,7	11,3	26,1	7,2	-7,8	15,3
210	CONC 06	0	0,2	0,3	0,4	209,2	11,6	1,3	59,1	36,4	7024,5	11,3	-88,3	9,6	52,0	15,2
211	MARD 08	0	19,6	11,2	11,9	23344,2	11,6	1,8	6,8	6,3	10315,6	12,2	24,1	-2,7	15,8	15,7
212	MARD 07	0	18,3	8,8	9,9	20758,9	11,6	1,2	12,9	11,4	3136,2	12,4	-18,6	23,0	-14,9	15,7
213	MARD 06	0	19,2	13,3	14,2	22421,9	11,7	1,4	11,4	10,6	7110,0	12,0	322,7	-3,8	29,4	15,5
214	CNSI 08	0	0,7	1,4	2,7	684,2	11,6	3,2	46,2	24,6	23613,5	10,8	92,2	19,6	12,5	16,3
215	CNSI 07	0	0,4	0,9	1,4	316,0	11,4	2,4	48,0	29,8	13476,9	10,5	67,7	-14,6	16,0	16,1
216	CNSI 06	0	0,3	0,5	1,0	185,2	11,2	1,4	90,7	43,0	6913,5	10,6	209,2	-12,8	19,1	16,3
217	COBJ 08	0	5,6	11,6	21,0	19656,4	12,9	2,1	51,7	28,5	46652,4	12,0	-1,8	36,5	68,1	17,5
218	COBJ 07	0	9,6	16,1	27,1	20939,0	12,5	1,9	50,4	29,9	32279,0	11,8	112,0	14,1	47,0	17,1
219	COBJ 06	0	6,7	8,7	17,6	12067,4	12,3	2,2	61,6	30,3	42260,1	11,8	126,2	40,8	88,4	17,0
220	CFED 08	0	0,3	0,2	0,3	204,3	11,5	1,4	49,7	33,3	12218,2	11,4	-84,4	12,5	5,7	16,2
221	CFED 07	0	2,1	1,6	2,1	1320,4	11,3	2,6	33,6	25,3	24718,5	11,3	-109,5	-5,1	22,3	16,1
222	CFED 06	0	-26,8	-15,9	-23,8	-10649,8	10,7	3,8	51,5	34,4	27594,0	11,1	-249,0	-13,9	-62,9	16,2
223	CORO 08	0	1,7	2,5	4,7	3297,2	12,3	1,3	80,7	43,7	11686,4	11,8	156,4	3,7	49,9	16,2

224	CORO 07	0	0,5	0,6	1,4	748,9	11,9	1,5	133,9	55,4	25490,9	11,8	162,8	42,7	143,9	16,2
225	CORO 06	0	0,5	0,3	0,5	271,7	11,0	4,1	67,2	39,1	24682,4	11,4	-97,6	29,5	-20,1	15,8
226	CNTE 08	0	10,6	15,5	16,6	2596,0	10,1	7,6	7,0	6,5	7178,2	9,7	17,9	-3,2	-6,6	16,2
227	CNTE 07	0	8,4	12,7	14,5	2024,7	10,1	3,8	13,2	11,6	5109,5	9,7	-24,6	-1,6	6,0	16,2
228	CNTE 06	0	11,8	16,6	22,5	2344,1	9,9	1,5	34,2	25,3	1736,1	9,6	-42,3	-11,4	-11,1	16,2
229	COBR 08	0	1,8	0,4	1,0	634,2	10,5	5,8	165,6	62,3	52506,3	12,1	25,4	-0,5	-2,1	14,9
230	COBR 07	0	1,4	0,3	1,2	505,9	10,5	3,4	299,0	74,9	45225,9	12,1	-82,3	-2,3	-0,6	14,9
231	COBR 06	0	7,9	1,6	6,6	2702,3	10,5	12,4	314,1	76,0	55322,1	12,0	287,7	-1,6	-3,3	14,9
232	MATA 08	0	0,1	0,1	0,2	78,8	11,3	1,7	99,5	49,0	11060,0	11,2	53,1	18,6	22,2	17,2
233	MATA 07	0	0,1	0,1	0,1	50,6	11,1	1,1	68,2	39,8	1864,4	11,1	-80,1	7,3	11,3	17,1
234	MATA 06	0	0,5	0,4	0,7	242,6	11,0	1,1	59,7	37,3	1562,9	10,9	163,2	50,5	21,8	17,0
235	MEGY 08	0	18,8	31,7	35,3	22820,5	11,7	6,4	11,5	10,3	40307,8	11,2	2,6	7,4	19,6	16,5
236	MEGY 07	0	22,0	33,2	47,3	19400,7	11,5	2,4	42,6	29,9	25341,6	11,0	239,2	51,2	416,9	16,4
237	MEGY 06	0	15,4	6,8	9,0	2681,5	9,8	2,4	33,1	24,9	13300,1	10,6	204,9	36,4	-40,6	16,0
238	MOLE 08	0	1,9	4,3	9,1	1646,6	11,4	2,1	85,1	39,9	11923,6	10,6	-50,7	27,8	12,5	16,0
239	MOLE 07	0	4,4	11,1	20,3	2931,9	11,2	1,5	76,5	41,7	3637,9	10,2	107,7	-13,7	28,5	15,7
240	MOLE 06	0	0,5	0,8	2,1	265,7	11,0	1,0	156,1	61,4	637,4	10,4	-39,4	-10,8	27,3	15,9
241	GUFX 08	0	0,7	0,6	1,6	729,4	11,6	0,9	153,6	59,7	-4702,1	11,7	10,6	2,0	-0,6	16,5
242	GUFX 07	0	0,6	0,6	1,4	502,7	11,3	1,0	146,6	58,6	1102,6	11,4	6,2	19,2	15,8	16,5
243	GUFX 06	0	0,7	0,6	1,7	496,7	11,3	1,0	163,0	61,0	-331,3	11,3	6,6	23,7	18,7	16,3
244	AMCP 08	0	3,1	2,5	5,4	9779,0	12,7	0,4	115,2	53,5	-116898,3	12,9	58,2	-4,0	12,2	18,4
245	AMCP 07	0	2,2	1,5	3,6	7276,9	12,7	0,6	135,5	57,3	-90410,6	13,1	-79,0	21,2	28,5	18,4
246	AMCP 06	0	13,6	8,7	17,7	42535,3	12,7	0,9	101,2	50,0	-15399,4	13,1	36,6	27,5	10,2	18,3
247	NAPO 08	0	0,9	0,6	0,9	1033,1	11,7	1,1	52,3	34,3	3052,7	12,1	331,8	15,7	27,4	17,8
248	NAPO 07	0	0,2	0,1	0,2	194,2	11,4	1,0	36,1	26,6	258,0	11,9	-21,8	52,5	29,0	17,7
249	NAPO 06	0	0,4	0,2	0,4	225,3	11,1	1,1	79,6	44,7	2081,6	11,4	2,9	30,2	1,6	17,3
250	NTEX 08	0	17,2	3,6	3,7	19572,6	11,6	2,6	3,3	3,2	27439,2	13,2	-9,7	0,0	-5,5	16,4
251	NTEX 07	0	18,0	3,9	4,1	19166,5	11,6	1,9	4,5	4,3	19434,9	13,1	63,1	91,3	32,2	16,4
252	NTEX 06	0	14,6	4,6	5,0	10187,4	11,2	1,6	10,0	9,3	12950,7	12,3	52,8	3,5	25,3	15,7
253	PETY 08	0	4,5	3,2	5,6	4354,1	11,5	1,2	74,1	42,6	9186,5	11,8	6,5	16,9	27,7	17,5
254	PETY 07	0	5,4	3,5	5,6	4130,8	11,4	1,1	59,2	37,2	4058,2	11,7	198,0	66,5	24,2	17,4
255	PETY 06	0	2,2	2,0	3,4	1481,0	11,1	1,1	74,2	42,6	3823,0	11,2	-36,2	6,0	19,7	16,9
256	PEHA 08	1	-17,7	-11,0	-14,7	-9192,3	10,9	1,6	33,2	24,9	12420,3	11,3	-56,7	18,5	28,2	13,9
257	PEHA 07	0	-52,4	-30,2	-36,3	-18404,3	10,6	2,5	20,2	16,8	15532,1	11,0	-183,2	-23,8	-40,5	13,7
258	PEHA 06	0	8,1	6,0	7,0	4802,2	11,2	3,8	15,7	13,5	30512,5	11,3	-110,4	-53,4	-77,8	14,0
259	PERO 08	1	-28,1	-11,5	-12,5	-10406,8	10,4	30,3	2,6	2,4	64079,6	11,4	-2,6	89,2	-14,2	13,8
260	PERO 07	1	-24,7	-22,3	-69,0	-4051,2	10,3	0,9	201,4	65,1	-1187,3	9,8	-52,1	-41,0	-43,8	13,2
261	PERO 06	0	-29,0	-27,5	-85,2	-5001,0	9,8	1,4	146,8	47,3	3024,4	9,8	-183,4	0,4	-37,7	13,7
262	BBGA 08	1	-133,7	-17,4	-18,7	-20128,0	9,4	18,7	2,2	2,0	395923,2	14,0	-31,6	-14,8	-37,2	19,4
263	BBGA 07	1	-122,7	-21,7	-23,0	-137386,8	11,0	27,1	2,0	1,9	252159,9	13,4	140,7	-19,6	-90,1	19,6
264	BBGA 06	1	-0,8	-1,2	-8,3	-3498,1	13,0	0,6	392,2	82,1	-94494,9	12,6	-99,2	-85,4	-58,5	19,8
265	REFR 08	1	-38,4	-2,5	-45,5	-36398,0	11,2	23,2	231,4	61,8	1399099,0	14,2	-43,8	-6,8	-71,1	14,9
266	REFR 07	1	-19,7	-4,1	-55,6	-64708,5	11,9	23,7	337,8	62,0	1502873,0	14,3	-85,6	-67,7	-86,3	15,0
267	REFR 06	1	-18,8	-9,3	-39,3	-14647,2	11,2	1,0	282,6	66,6	-3345,8	12,0	-46,1	-40,4	-46,3	16,1
268	ROMS 08	1	-188,8	-7,6	-37,0	-33184,1	10,1	0,1	387,0	79,5	-313982,5	13,0	84,7	173,0	-9,7	16,0

269	ROMS 07	1	-190,1	-11,2	-39,6	-8572,8	9,2	0,2	253,3	71,7	-42070,7	11,2	-9,9	79,0	-33,5	15,0
270	ROMS 06	1	-140,3	-22,3	-52,5	-8904,0	9,0	0,3	163,6	69,4	-19320,2	10,6	-9,0	377,2	-25,1	14,4
271	SALT 08	1	-228,1	-3,6	-3,7	-54869,4	10,1	0,1	4,6	4,4	-57143,0	14,2	42,4	219,2	-33,2	15,9
272	SALT 07	1	-107,0	-8,0	-8,9	-32099,7	10,5	0,2	11,7	10,5	-26996,2	12,9	158,4	-7,3	60,2	14,7
273	SALT 06	1	-66,3	-2,9	-3,2	-12424,5	9,9	0,2	10,5	9,5	-32778,8	13,0	-45,9	486,2	-11,2	14,8
274	SENY 08	1	-5,0	-2,2	-3,1	-7663,2	12,1	0,5	41,7	29,4	-53812,8	12,8	33,9	80,3	57,6	17,0
275	SENY 07	1	-5,9	-2,9	-4,1	-5995,5	11,7	0,6	40,0	28,5	-24971,7	12,2	51,3	406,8	135,7	16,4
276	SENY 06	1	-9,2	-9,8	-12,8	-4161,0	10,9	1,8	25,9	19,8	6753,6	10,7	-33,2	-11,7	-21,2	14,8
277	SEBZ 08	1	-10,4	-6,2	-6,5	-4233,4	10,6	7,6	4,8	4,6	20462,1	11,1	-21,7	8,4	-39,5	15,1
278	SEBZ 07	0	-8,1	-8,6	-11,6	-4186,1	10,8	1,3	34,3	25,6	4113,2	10,8	-129,6	-7,4	52,9	15,1
279	SEBZ 06	0	0,1	0,1	0,1	28,5	10,3	1,7	30,0	23,1	6928,5	10,7	-24,5	1,7	1,8	15,1
280	SINT 08	1	-21,1	-14,0	-19,5	-15425,2	11,3	1,9	42,0	30,2	25537,2	11,6	121,5	-14,4	-3,1	16,1
281	SINT 07	0	-9,2	-5,4	-7,4	-7298,5	11,3	2,1	38,6	28,4	33651,6	11,8	-107,3	8,6	19,9	16,2
282	SINT 06	0	1,3	0,7	0,8	1021,0	11,3	2,5	25,5	21,9	34400,9	11,9	-78,9	85,1	11,4	16,1
283	SOMR 08	1	-43,6	-54,1	105,3	-21831,4	13,0	0,5	-296,3	152,2	-287175,9	12,9	252,3	-28,4	-18,1	19,8
284	SOMR 07	0	-3,8	-4,1	-207,2	-22215,0	13,4	0,9	302,0	98,6	-69789,6	13,2	-172,6	124,7	202,9	20,2
285	SOMR 06	0	15,7	12,6	92,9	30308,7	12,3	0,8	345,9	87,6	-40999,5	12,4	-171,8	80,9	82,0	19,4
286	TMDF 08	1	-18,6	-12,8	103,8	-11703,0	11,2	0,3	-318,3	112,8	-71132,7	11,4	12,0	7,1	13,2	17,0
287	TMDF 07	1	-18,7	-12,2	-129,6	-7085,4	10,6	0,4	361,9	90,5	-33900,1	11,0	13,7	7,7	15,2	17,0
288	TMDF 06	1	-19,0	-11,6	-33,5	-4715,6	10,2	0,4	188,3	64,8	-14792,1	10,6	26,0	10,7	-16,6	16,9
289	TRCL 08	1	-47,9	-29,2	-91,2	-4103,6	9,4	0,8	211,8	67,9	-2090,6	9,5	245,6	28,8	-44,5	15,9
290	TRCL 07	0	-4,1	-5,8	-8,9	-597,6	9,6	1,4	53,1	34,7	1382,0	9,2	-152,1	-4,1	-2,1	15,7
291	TRCL 06	0	0,3	0,4	0,6	36,5	9,5	1,6	46,6	31,8	1452,7	9,1	-69,8	2,1	-9,1	15,7
292	TUOL 08	1	-216,8	-9,5	-16,1	-12019,4	9,0	0,1	70,5	41,4	-49830,1	11,8	10,0	5,0	-55,1	15,5
293	TUOL 07	1	-211,0	-9,0	-12,7	-9767,3	9,1	0,1	40,4	28,8	-27814,3	11,6	49,9	20,8	-71,3	15,4
294	TUOL 06	1	-40,4	-7,3	-9,9	-6958,4	9,8	0,3	35,3	25,9	-18273,1	11,5	132,3	38,8	-22,1	15,3
295	URUL 08	1	-43,5	-20,0	-55,7	-17122,3	10,6	1,7	168,0	60,2	9778,0	11,4	53,7	16,1	-13,1	17,3
296	URUL 07	1	-24,6	-15,1	-33,2	-7640,7	10,5	1,3	114,8	52,1	3732,9	10,8	116,0	19,2	-11,6	17,2
297	URUL 06	1	-10,1	-8,3	-14,2	-2692,1	10,5	1,0	69,8	40,9	577,8	10,4	-11,5	7,4	-0,5	17,0
298	INOX 08	1	-12,8	-6,7	-10,6	-13684,2	11,6	1,0	51,7	32,4	1822,4	12,2	-50,9	7,8	25,8	16,7
299	INOX 07	0	-32,8	-14,6	-19,4	-21157,8	11,1	1,1	32,8	24,7	2213,7	11,9	-240,1	-4,0	26,8	16,6
300	INOX 06	0	0,2	0,1	0,1	68,8	11,0	2,3	16,8	14,5	15883,8	11,7	-99,9	-39,1	12,0	16,6