An Overview on Solvency Supervision, Regulations and Prediction of Insolvency

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Abstract. This paper presents an overview of solvency supervision, including the effects on the solvency position of insurance companies, the objectives of solvency regulations and the role of government for protecting the public in case of insolvency. It also presents the efforts of the European Union (EU) to reform the existing regulatory system of Solvency I and create a new system of Solvency II. Statistical methodologies such as discriminant analysis (DA), logistic regression (LR) and multinomial logistic regression (MLR) have been used for predicting financial distress of insurance companies based on balance sheets and other financial characteristics. An application of the above statistical methodologies could provide a better insight to the future of merged companies. Regression techniques have also been applied to estimate the relationship between some important ratios with other financial characteristics. The estimated regression line can be considered as the industry equation (norm) and can be used to identify insurance companies that deviate substantially from this estimated relationship. Through our study we consider the case of the insurance system of Greece.

Keywords: Solvency II, statistical methodologies

1 INTRODUCTION

In recent years, the increased number of insurer insolvencies has led solvency to be one of the most important topics of the insurance industry. Most of the studies were implemented in the United States insurance market. The National Association of Insurance Commissioners (NAIC) in the United States played the role of monitoring the financial condition of insurers for the purposes of detecting financial distress and preventing insolvency. NAIC introduced Insurance Regulatory Information System (IRIS) ratios, the risk-based capital (RBC) system, and the Financial Analysis and Surveillance Tracking (FAST) scoring system, to classify solvent and insolvent insurers. Best's (2007) ratings also provide an objective opinion on the ability of a specific insurance operation to meet its ongoing obligations to policyholders.

In the literature of insurance science, there are several research papers that present NAIC's introduced systems (IRIS, RBC, FAST), as well as Best's rating and other statistical techniques, to predict insurer insolvencies. Harrington and Nelson (1986) used a regression analysis to estimate the relationship between premium-to-surplus ratios and insurer characteristics including asset and product mix variables. Ambrose and Seward (1988) used multivariate discriminant analysis in order to compare the insolvency prediction abilities of Best's ratings and a two-stage prior probability approach. Ambrose and Carroll (1994) examined the efficiency of Best's recommendation, IRIS ratios, and other financial measures in their statistical ability to classify solvent and insolvent life insurers. Butsic (1994) introduced solvency measurement for property-liability RBC applications and developed practical methods for setting RBC standards using the expected policyholder deficit as the solvency measure. Brockett et al. (1994) introduced a neural network artificial intelligence model as an early warning system for predicting insurer insolvency. Cummins et al. (1995) conducted an empirical analysis between property-liability insurer insolvency risks and RBC. Grace et al. (1998), based on the RBC system the FAST audit ratio and IRIS ratios, classified and prioritized insurance companies for more in-depth financial analysis. Cummings et al. (1999) compared RBC system, the FAST audit ratio and a cash flow simulation system developed by them. Barniv et al. (1999) provided a method of constructing confidence intervals for insolvency probabilities in the insurance industry. Browne et al. (1999) focused on identifying important predictor variables such as interest rates, real estate and stock market returns, personal income and unemployment, for identifying insurers at higher risk of insolvency. Chen and Wong (2004) investigated solvency of general property-liability and life insurance companies in Asia (Japan, Singapore, Malaysia and Taiwan). Schmeiser (2004) developed an internal management approach for property-liability insurers that is based on dynamic financial analysis. Sherris (2006) considered links between solvency, capital allocation and fair rate of return in insurance.

The last few years there is a great effort of the European Union to reform the existing regulatory system of Solvency I and create the new system of Solvency II. Our study considers the case of the insurance system of Greece. Illustrating the case of Greece, we illustrate similar situations of countries, which undergo a transition period due to the reform of their insurance market regulatory system, towards the new supervisory system of EU, the Solvency II.

The case of Greece also represents similar cases of southern European countries, such as Spain and Portugal. These countries of southern Europe, after experiencing years of

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dictatorship (until the year 1974) joined the European Community (EC). After a few years of democratization and liberalization, Greece joined the European Community in 1981, Spain and Portugal in 1986. Since becoming members of EC, the three southern European Countries have received substantial financial assistance that has helped them in their efforts to modernise their economies and consequently to reform their insurance system towards the new supervisory system of EU, the Solvency II. According to a survey conducted by the Creditreform (2008) economic research organisation in the EU, these southern countries (including Italy) have the lowest insolvency rates.

The reform in Greece is also different from the reform in central and northern countries (especially Scandinavian countries) that was implemented much earlier than the rest of Europe. Even the implementation of Solvency II to Scandinavian countries can not bring much difference to the already reformed insurance system of these countries. A study conducted by Altren and Lyth (2007), about the Swedish non-life insurance industry, indicated that no obvious benefits related to the potential effects above could be realised by complying with Solvency II. The case of southern European countries and especially that of Greece is different than the case of former communist countries in Europe who moved from centrally planned economies i.e., from a bureaucratic monopoly with inefficient performance, to market economies (see Venard et al., 2008).

The purpose of this article is to present an overview for solvency supervision in Greece. The first main contribution of the paper is to present the effects of solvency position of insurance companies, the objectives for solvency regulations and the role of the government in protecting the public against insolvency. An additional contribution is to present the effort of the European Union to reform the existing regulatory system of Solvency I and create the new system of Solvency II.

The second main contribution of the paper is a) to predict insurer financial distress (including insolvency), by using statistical methodologies such as discriminant analysis (DA), logistic regression (LR) and multinomial logistic regression (MLR), and b) to estimate the relationship between some important ratios with other financial characteristics by applying regression techniques. The estimated regression line can be considered as the industry equation (norm) and can be used to identify insurance companies that deviate substantially from this estimated relationship. The statistical methodologies that have been applied may also give a better insight to the financial position and the future of merged companies.

The sample of firms used in our analysis consists of 31 healthy companies, 9 insolvent (bankrupt) and 14 merged ones. We selected solvent companies that operated from the period 1996 and remained healthy through the year 2002. So, in total we had 31 healthy companies for 7 consecutive years of operation (a total of 217 solvent cases) and 23 merged and insolvent cases. The selection criteria for the financial variables (ratios) used in our analysis were the popularity in the literature and potential relevance to our study. Most of our empirical results confirmed the real situation of the insurance industry of Greece from the year 1996 through 2002.

The paper is organized as follows. Section 2 presents a brief history on the position of regulatory authority of Greece, its historical appearance as well as its operation, including the supervision of insurance companies, its reform and the effort for its harmonization with EU Solvency II standards. In the same section we illustrate the effects of solvency position, the objectives of solvency regulations, as well as the role of the government for protecting public against insolvency. In Section 3 we apply statistical techniques for predicting insurer's insolvencies with data provided from the National Database Association. Finally, some discussion and concluding remarks are given in Section 4.

2 EC TOWARDS SOLVENCY II (The case of Greece)

The first attempt to establish the Greek Supervisory Authority was made in 1909 and allowed only insurance companies with head offices in Greece. Shortly after, in 1910, branches with head offices abroad were allowed to operate in Greece. In 1917, for the first time a government ordinance appeared with regulations concerning the operation of insurance companies (see the Ministry of Commerce of Greece website). In 1976, after two years of a post-dictatorship period of democratization and liberalization, Greece reformed the supervisory authority that became an independent entity (with strict rules), and since then it is under the Ministry of Commerce and Development.

The Greek government has taken some important actions, in order to have a better and more credible control of the operation of insurance companies, which include: a) the increase of the minimum guarantee fund (MGF) required for the operation of an insurance company (today in Greece, the amount of MGF has been raised to three million Euros), b) the establishment of an auxiliary fund for the purpose of having a better and faster settlement of claims, c) the establishment of a new committee aiming to adapt and modernize government legislation regarding the operation of the insurance companies and to provide the public with a minimum level of protection from the adverse affects of insurer insolvency, d) the periodical supervision of the solvency of insurance companies, e) the creation of a complaints network for out-of-court dispute settlement.

The Insurance Supervisory Authority of Greece controls about 72 insurance companies with head offices in Greece, and also controls 30 branches of insurance companies with head offices abroad. The departments under supervision are: a) the department of management supervision of insurance companies, which monitor the operations, balance sheets, agents and brokers, the cooperation with supervision authorities of countries members of the EC, the investigation of complaints, b) the department of technical control of insurance companies aiming to control the sufficiency of technical reserves, of solvency, the expansion of the company's function and cooperation with international insurance organizations.

Today the Greek Government and in general the European Commission (EC) makes an effort to create a common "universal" approach, the Solvency II, which is the European solvency system for insurance undertaking and is a reform of the existing solvency rules of the European directives (Solvency I), aiming at harmonizing the regulations and differences of the Member States and provide and support market stability. The KPMG (2002) solvency study for the EC provides an overview of the methodologies suggested to assess the overall financial position of an insurance undertaking from the perspective of prudential supervision.

Solvency II developed in an analogue approach to Basel II, which the regulatory bank capital adequacy rules system for banks. Suarez et al. [2005) provided an overview of the Basel II framework and presented different approaches which can be used to determine the amount of regulatory capital needed for the equity exposures.

The perspective of Solvency II includes the main types of risks to which an insurance undertaking is exposed as well as techniques for managing the type of risks. It also (i) deals with a number of issues related to reinsurance and its integration in a future harmonized solvency system, (ii) develops methods by which insurance undertakings control or reduce risks, (iii) promotes the risk management, (iv) describes the accounting requirements in accordance with International Accounting Standards (IAS) within the regulatory system, (v) assigns the role of rating agencies and other market mechanisms and (vi) develops solvency capital methodologies.

The last few years, based on a general framework, several studies were ordered by the EC in order to develop regulations and guidelines for solvency supervision. Solvency II is the new set of insurance regulations that aims to set a common standard regarding solvency capital and risk management for insurance companies within the European Union. Based on proposals of Solvency II, insurance companies may also apply internal models approved by their supervision authorities. Linder and Ronkainen (2004) provide a nice description of the current state of affairs of Solvency II as well as a general outline of the future EU solvency system.

The Committee of European Insurance and Occupational Pensions Supervisors (CEIOPS) has been requested from EC to provide a framework for the development of the new solvency system (Solvency II) for life assurance, non-life insurance and reinsurance undertaking. The CEIOPS (2006a, 2006b) proposals provide the EU with methodology and sufficient technical advice for the implementation of Solvency II. Implementation of Solvency II is expected around the year 2012.

Eling et al. (2007) provide a nice overview of the Solvency II process outlining the specifics of Solvency II as they currently stand and suggest important areas of future research. Sandstrom (2007) presents a historical review and some pragmatic solutions for Solvency II. Schreckenberg describes the current status of the development of Solvency II, and Pfeifer and Strassburger (2008) describe stability problems with the suggested Solvency Capital Requirement (SCR) aggregation formula.

2.1 Effects of Solvency Position and Withdrawals of Licenses of Insurance Companies

The solvency position is affected by most economic activities and decision making processes which are: ratemaking, evaluation of technical reserves, risk undertaking, reinsurance activities, investments and sales. The solvency position can also be affected by the country's economy, new legislations, inflation and interest rates.

Factors affecting insolvency are: catastrophes, natural disasters (earthquake, floods), bad management, which include bad operation of the company and bad (risky) investments, competition, a long period of low interest rates resulting in the reduction of investment income, fraud against insurer, economic instability of the country, increase of actuarial liability. With the appearance of any kind of catastrophe, a crash can happen beyond any prevention, even imagination. Even a high increase in capital can do practically nothing against catastrophes, so regulation has to foresee exposure rather than capital.

When insolvency of an insurance company is inevitable, the mission of the supervision authority is not to prevent the forthcoming insolvency, but to minimize public harm, which usually means taking insolvent insurer out of the market place promptly by withdrawing its license. The reasons for which the likelihood of insolvency of insurance companies increased were that, in the middle 70's a new political era in Greece led to the liberalization of the insurance industry and the fast growth of the economy. Companies with no previous management experience entered into insurance

business with a high cost of operation, having to face a new competitive world. Old-fashion actuarial techniques were used for premium estimation and techniques for the estimation of the technical reserves were premature. Because of this, some companies undertook higher risks they could afford. A lack of strict legislation led to the appearance of new companies, which did not have the appropriate management tools and experience to operate in the Greek market. Even today with the global economy and the convergence of natural insolvency laws, Greece does not have fully integrated international laws. Stewart Economic Insurance reports (1998, 2003), describe similar situations of the insurance industry in the United States, during the last few decades, as well as tricks for delaying insolvency.

The Greek government, after evaluating balance sheets, operating performances and business profiles, has decided not to allow certain insurance companies to conduct normal ongoing operations any longer. Court law placed these insurance companies under liquidation order, merger, acquisition, or absorption by a parent or a competitor company. Some others have been placed under supervision and control and were suspended. The number of insurance companies that have failed since 1981 through today is about fifty (50). Eighteen (18) of them failed during the decade of 80's, with peak years in 1982-1983, twenty-six failed the decade of the 90's, with peak years in 1992-1997 and the rest failed in the early 2000's. Most of them went bankrupt following a government ordinance. Half of them are still under liquidation.

These insurance companies got into financial trouble because of competition or they did not know how to deal with fundamental problems. Under this distress, they acted desperately and undertook risk that they could not cover. Insurance companies with financial distress either went out of business or have been merged. The effects of the crash of the stock market in Greece, in 1999 led some insurance companies to go bankrupt few years later. Also, during the period 1996-2001, some companies, in order to increase their market share applied policies of low premiums and high commissions. Not surprisingly, most of them failed few years later. Almost half of the companies that went bankrupt had a small duration of operation in the Greek market, a fact that indicates that since the beginning of their operation, they did not have the appropriate standards for being in the market. Companies that could not figure out how to respond and survive to such distress were not necessarily dishonest or incompetent, although, few of them did have fraudulent incentives.

Most decisions for withdrawing the license of an insurance company were based on balance sheets and observations of charter accountants. No information was available for each individual insolvent company, so we had to rely on government ordinances, published in government newspapers during the years 1980-2002. Withdrawals have been accomplished because of the following main reasons: a) deficiency of reserves, b) systematic violation of the annual accounting balance sheet, c) not meeting the minimum capital requirement or the minimum amount of the solvency margin, d) not having the ability to meet their ongoing obligations to policyholders, e) delaying payments, f) miscalculating the outstanding claims (underestimating of claims and suppressing reserves in order to show better profits, not having the appropriate cash flow for operation), g) not having the minimum guarantee fund, h) not contributing to subsidiary fund or to the International Bureau of Insurance. More details were presented in Pitselis and Maragou (2004).

In Greece, as in many countries there was a tendency of trying to prevent insurer's insolvency. Usually, the regulators delay to act on a company's financial difficulties, because bankruptcy affects a large number of people such as, policyholders (about whether the terms of their policy will be fulfilled); investors (about the value of their shares and expectation of dividends); employees (about the security of their jobs); managers and directors (about their reputation as well as their shares); other competitors (about the impact of insolvency on premium rates); reinsurers: (about the collection of reinsurance premium, direct settlement of claims); Government (about the insurance industry and its role in the economy of the country); Supervisory Authority (about the regulations of monitoring insurance companies and a methodology for predicting insolvency) [see Taylor (1987)].

Facing financial trouble, the management of the company reacts in order to prevent or delay insolvency. The first reaction is to change strategy and the second to "cook" accounting books. During the period of delay, the management of the company often takes greater risks in order to attempt a recovery and facing a financial trouble, acts often desperately in order to prevent insolvency. What actually happens is that management starts gambling and these results in more harm to the public. A troubled company will get tougher on claims. As long as a claim is in dispute, there is cash in hand and reserves to manipulate [see Stewart Economic Ins Report (2003)].

Another reaction is to use reinsurance, which removes losses of the primary company's balanced sheet. In this way the company can increase its business without raising additional capital. All these techniques increase assets, decrease liabilities, accelerate income or postpone expenses. The delay rarely helps and usually ends with a government ordinance.

Sometimes, when a company is known to be failing, regulators split the company's business books into parts, the profitable and the unprofitable and place the two parts in

two separate companies. From time to time the supervisory authority has to force the parent company to absorb its affiliated companies. The merging can also happen for accounting or management reasons (reduce the cost of operation), or for tax purposes. Most of merged cases observed in Greece were affiliated companies absorbed by their parent companies to minimize the cost of operation and to improve management. However, we had few affiliated companies with financial problems that were merged and absorbed by their parent companies.

A phenomenon which sometimes appears in the insurance industry, and which can create a lot of damage is insurance fraud. There is an extensive literature concerning policyholder's fraud against an insurance company, but there is not much concerning insurance fraud against the public or against the government. Fraud against the public can be revealed when the financial statements of a company do not reflect its true economic value.

Example 1: Some insurance companies with fraudulent purposes modify the values of some financial characteristics in the balance sheets (cooking the books), in order to avoid regulatory action. During that period of time they collect premiums and delay or refuse payments. In most of the cases consumers end up in dispute with these companies, resulting in long duration lawsuits against insurers. In the mean time the insurer declares bankruptcy and leaves with most of consumers' money and "goes to Brazil".

Another kind of fraud can appear during the insurance marketing selling process, where a product requires a few steps until it arrives from brokers, agents and sales persons to consumers.

Example 2: Individuals (pretending to be brokers or agents) use names of reputable financial institutions and insurance companies for fraudulent purposes (scams). Often, these scams involve the placement of classified advertisements in local newspapers, or personal communication, that offer life-health insurance coverage with relatively small amount of money on the condition that an advance deposit or processing fee has to be paid immediately. Then insured people receive a receipt under the name of the pretending agent and realize that they are victims of fraud in a case of a claim.

Example 3: Some organizations, with fraudulent purposes, advertise that they have found a loophole in the tax rules that allow for tax-free withdrawals from benefits that are covered by a pension plan. These members of the pension plan realize that are victims of some fraud when they want to exercise some of their privileges provided by the plan.

2.2 Objectives for Solvency Regulations, Managing Insurance Insolvency and the Role of Government

The objectives of solvency regulations are: a) to prevent company insolvency, b) to protect the public from financial loss resulting from financial distress of an insurance company, c) to assure the public of fair and equitable treatment by insurance companies, d) to protect the public from unfair policies, e) to examine, monitor and investigate the affairs of insurance companies, f) to provide legislations and regulations which will insure equitable pricing and reasonable underwriting standards, and g) to follow the international accounting standards (IAS).

Actuaries should calculate the probability of bankruptcy (ruin theory), determine the initial capital allocation, check the adequacy of reserves, perform sensitivity analysis based on different levels of interest rates and estimate the risk exposure of each line of business.

Government has the primary responsibility to regulate insurance companies, introduce strict legislations, enhance disclosure of compensation, review the relationship among insurers and brokers, agents and sales person, enhance public confidence in the market place. Many insurance companies having their head offices in EU, or third countries have established branches in Greece. The Greek government has taken legal actions against insurance companies that do not meet certain criteria. Greece is moving towards Solvency II, in order to support the supervisory authority toward harmonization of solvency requirements between member states of the EU.

Greece, as well as countries which undergo a transition period due to the reform of their insurance market regulatory system, have to take into consideration the future three pillar system approach. The first pillar concerns the achievement of harmonized and transparent technical provision in the EC. This achievement requires, in addition to old techniques, advanced statistical techniques as well as stochastic financial methods. The experts for Solvency II have proposed two capital levels requirements: a main target level solvency requirement and a minimum capital one. The target capital should reflect the economic capital that a company needs to operate safely and the minimum capital level should serve as a trigger level for severe regulation action [see CEIOPS (2007b)].

The second pillar requirements will include principles for internal control and sound risk management of insurance undertaking (see CEIOPS (2007a)). The third pillar requirements will be closely aligned to the contents of the other two pillars including disclosure and transparency of the solvency II plan [see Linder and Ronkainen (2004)].

The Greek government in compliance with the EU guidelines developed regulations that are required to be followed by the insurance companies. More specifically, regulations may prescribe: a) the valuation of assets and liabilities for the purpose of ordinance of the required margin of solvency and of methods of calculation, b) the minimum guarantee fund for each line of business, c) the methods of calculating technical reserves including mathematical reserves, d) the nature of assets which may comprise solvency margins, guarantee funds or technical reserves, e) the places where the assets are to be kept and the nature and appropriateness of such assets in relation to the currencies in which liabilities are to be met, f) the deposits to be made by insurers which have their head offices outside the EC and the investment of such deposits, g) the form and contents of annual profits and losses of income and expenditure accounts and balance sheets and auditors' and actuaries' reports and statements and any other documents, h) the ways in which accounts and balance sheets are monitored and g) the fees to be paid under this ordinance and the person to whom they are to be paid.

Now since international accounting standards (IAS) are applied, old tactics are being questioned, managements are turning over and old accounting tricks become out of fashion.

3 DATA AND METHODOLOGY

Financial data of automobile insurers were obtained from the Bulletin of the General Secretariat of Trade, the Direction of Insurance Companies. When this project started the available data were from the year 1996 through 2002 (today the available data is through the year 2004). Initially, we collected data for 70 insurance companies. The insurance companies, that were chosen, were considered to be healthy (solvent) according to the Supervisory Authority of Greece. Data also collected, for all 34 insurance companies that went bankrupt or were absorbed (merged) by their primary (or by a competitor) company, for the same period. The year 2002 there were no bankruptcy cases, but we had 6 cases of merging.

The difficulties that we faced during the data collection and analysis process were: a) the available data were from the year 1996 through 2002 and were not in electronic form, b) the number of companies (especially insolvent ones) was relatively small, c) we had available a restricted number of financial variables, d) a lot of missing values for some financial characteristics (as reserves, IBNR etc.), especially for data of insolvent companies, e) almost half of insolvent companies included in our analysis went bankrupt the year 1997, so the available data were only for one year before bankruptcy for those companies and f) we could not analyse life and non-life companies separately, due to the limited availability of financial data.

Our primary purpose was to examine the financial characteristics (independent variables) that distinguish solvent from insolvent companies. The variables that were selected are those that were available in the Bulletin and that were appropriate for our estimation. The insurance companies that were selected had their head office in Greece. After examining our data (validity of data, missing values etc.) we ended up with 31 healthy companies, 9 insolvent (bankrupt) and 14 merged ones. We selected solvent companies that operated from the period 1996 and remained healthy through the year 2002. So, in total we had 31 healthy companies for 7 consecutive years of operation (a total of 217 solvent cases) and 23 merged and insolvent cases. Some preliminary results of the investigation of insurer insolvency in the Greek market were presented in Pitselis and Maragou (2004).

Supervision of solvency and predicting insurer's insolvency were based on discriminant analysis (DA), logistic regression (LR) and multinomial regression (MLR). These models have been discussed extensively in many articles in the past. In the following we give a brief description of these models.

Discriminant Analysis (DA) is a procedure used to classify an object into one of several distinct sets of objects to study the differences between these objects with respect to several variables simultaneously. The characteristics used to distinguish among the groups are called "discriminating variables". These variables must be measured at the interval or ratio level of measurement, so that means and variances can be calculated and so that they can legitimately be employed in mathematical equations. The discriminant function takes the form

$$z = b_1x_1 + b_2x_2 + ... + b_nx_n$$

and transforms individual ratio values to a single discriminant score or z value which is then used to classify the object where, b_1, b_2, ... , b_n are the discriminant coefficients and x_1, x_2, ... , x_n are the independent variables and usually are individual ratio values. The final step in any study of this kind is the classification of the objects into one of the original groups. The discriminant model is considered accurate if members of particular groups are reclassified into these same groups. It is assumed that the feature vectors have a Gaussian distribution.

The following tests have been used during the application of DA: Wilks's lambda applied for testing the equality of group means. Box's M test used to test for equality of the group covariance matrices. The significance level was obtained from the F distribution (see Cooley and Lohnes, 1971).

For variable selection a stepwise method was applied. Stepwise regression is a statistical technique for determining

which variables to include in the regression model and uses automatic variable selection procedures to suggest what model to use. With this method the variables that are not important are excluded from the regression model. There is no guarantee that the subset selected is "best", regardless of the criterion used to make the selection. Eligible variables with higher inclusion levels (F-to enter) are entered before eligible variables with lower inclusion levels. A variable is considered eligible for removal in the model if its F-to remove is less than the F value for removal. According to our criterion a variable is entered in the model if the value of F is bigger than 3.84 and removed if the value of F is less than 2.71. Once a set of independent variables has been selected, Fisher's linear discrimination function is computed [see Johnson and Wichern (1982)].

Altman (1967, 1968) was the first who proposed discriminant analysis (DA) for failure prediction in 1968. This study was of much interest as it was the first to relate the classification offirms to more than one variable, using DA. The DA model has
also been used by Trieschmann and Pinches (1973) and Carson and Hoyt (1995) to predict financial distress for property-liability and life insurance insurers, respectively.

Logistic Regression (LR) is useful for predicting a binary response, the dependent variable, from a set of independent variables (continuous or categorical predictors). LR is a preferred method in cases when normality assumptions under multivariate analysis are violated. The linear logistic model assumes a dichotomous dependent variable Y with probability p_i for the i-th case, with

$$p_i = \frac{1}{1+e^{-x_i'\beta}}$$

or equivalently,

$$Y_i = \ln\left(\frac{p_i}{1-p_i}\right) = x_i'\beta,$$

where x_i' is a row vector of the observed independent variables for the i-th case, β is a px1 vector of regression coefficients. Similarly to DA, for variable selection stepwise method has been applied to LR. A score statistic was used to select variables for entry into the model. Wald's statistics is calculated for the variables in the model to determine whether a variable should be removed. The asymptotic distribution of the score/Wald statistic is a chi-square with degrees of freedom equal to the number of variables involved/estimated [see Johnson and Wichern (1982)].
Press and Wilson (1978) had found that under non-normality the logistic regression provides better classification rates than discriminant analysis and presented theoretical arguments for using logistic regression with maximum likelihood estimation compared to using linear discriminant analysis, in both the classification problem and the problem of relating qualitative to explanatory variables.

Multinomial Logistic Regression (MLR) can be applied in cases in which we want to classify subjects based on a set of independent variables. It is similar to logistic regression, but it is more general since the dependent variable Y is not restricted to two categories. Suppose a dependent variable has g categories. One value, usually the value with the highest frequency, is used as a reference category. The probability of other categories is compared with the probability of the reference category. For g categories calculation of g-1 equations is required, to describe the relationship between the dependent variable and the independent variables. For the binary dependent variable, the probabilities for the two categories Y=0 and Y=1 are given by [see Jobson (1992)]

$$p(Y=1) = p = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}}$$

and

$$p(Y=0) = 1-p = \frac{1}{1+e^{x_i'\beta}}.$$

$$\frac{p}{1-p_i} = e^{x_i'\beta}, \text{ or } \qquad \ln\left(\frac{p_i}{1-p_i}\right) = x_i'\beta.$$

Similarly, for the case of g categories, we define dummy variables $Y_j, \quad j=1,...,g,$ where $Y_j = 1$ if the observation is in the category $j,$ and $Y_j = 0$ otherwise. We define conditional probabilities $p_1, p_2, ..., p_g,$ where

$$p(Y=1) = p_j = \frac{e^{x_i'\beta_j}}{1+\sum_{j=1}^{g-1} e^{x_i'\beta_j}}, \quad j=1,...,(g-1)$$

and

$$p(Y=g) = p_g = \frac{1}{1+\sum_{j=1}^{g-1} e^{x_i'\beta_j}}, \quad j=g.$$

Stepwise Linear Regression is an automatic search procedure for selecting which variables to include in a regression model. The forward stepwise regression is most widely used of the automatic search methods. This search

method develops a sequence of regression, at each step adding or deleting an X variable. The criterion for adding or deleting an X variable can be stated equivalently in terms of error sum of squares reduction, coefficient of partial correlation, or F statistic. This procedure ends with the identification of a single regression model as "`best". The backward stepwise procedure is the opposite of forward stepwise regression. It begins with the model containing all potential X variables and ends with a single regression model. For more details see Neter et al. (1994), or any other book in regression linear model.

4 EMPIRICAL RESULTS

In this section applications of the above-mentioned models are applied in order to predict insurer insolvency. Before analyzing the results we provide a summary statistics for our data. Table 1 presents a descriptive statistics of the initial variables (financial characteristics) that have been chosen for the analysis.

The description and the name of variables are given in the first two columns, while the mean and standard deviation of healthy, merged and insolvent companies are illustrated in the rest of the columns. The values of these variables are in thousands of Euros. Here we can observe the differences in means and standard deviations among insolvent, merged and healthy companies. More specifically, we can observe that on average, the net profit before tax, for both merged and insolvent companies, is negative, and the mean value of reserves for merged companies is small, while for insolvent companies is negligible.

Based on the initial data of 17 variables, as were presented in Table 1, we have created 12 new variables (ratios) for our further analysis as ratios of our initial variables presented in Table 1. The choice criteria were the popularity in the literature and potential relevance to our study. For example, the ratio of Total of Debt (TD) over the Total of Assets (TA) is denoted by TD_TA. Similarly, we can define the rest of the 12 variables (ratios) as illustrated in the Table 2 together with some descriptive statistics.

Table 3 presents Pearson's correlation between the above-presented variables. As we can see OC_TR and TA_TR are the highest positively correlated variables followed by the pair of variables NP_TA and NP_WP. The most negatively correlated variables are TA_EP and TC_EX, followed by the pairs NP_TA and EX_EP, and I_EP and TC_EX, respectively.

Table 1: Summary Statistics (in 1000 of Euros) for 1996-2002

		Healthy n=217		Merged n= 14		Insolvent n=9	
Variable Description	**Variable**	**Mean**	**StDev**	**Mean**	**StDev**	**Mean**	**StDev**
Total of Claims	**TC**	23292.19	42392.4	15588.73	16466.97	4666.74	4349.05
Total of Investment	**TI**	52570.75	142491.83	19581.19	24697.78	2079.54	1412.93
Total of Assets	**TA**	83082.77	199472.86	15588.73	42370.39	7702.76	6686.26
Equity Capital	**EC**	6831.81	12790.36	4527.13	5311.84	1003.94	672.47
Own Funds	**OF**	13781.86	24722,04	4612,18	7099,25	1133,04	1023,11
Technical Reserves	**TR**	4361.22	12015.47	620.25	978.34	46.73	49.37
Current Risk	**CR**	9249.02	18776.73	4643.26	5898.55	1320.81	1675.66
Outstanding Claims	**OC**	24929.95	75557.13	12533.27	12765.65	2101.29	2735.51
Total of Provisions	**TP**	57491.01	159604.77	26293.11	31818.19	3480.56	3621.87
Total of Debt	**TD**	10760.98	18291.26	17139.91	18881.52	5140.39	4444.19
Written Premium	**WP**	26871.33	47891.30	15117.23	16046.77	3802.59	3121.59
Earned Premium	**EP**	39688.27	74006.64	24265.78	29665.41	8174.52	6895.49
Incoming	**I**	29618.65	54520.32	17139.91	18881.52	5140.39	4444.19
Paid Claims	**PC**	16842.63	31434.68	8721.27	8276.71	2165.12	1666.56
Expenses	**EX**	26370.51	47377.26	17145.68	17507.37	4694.76	3840.04
Net Profits Before Tax	**NPBT**	1661.10	5947.01	-867.51	2830.59	-272.48	559.11

Note: Descriptive Statistics for the primary variables that where available and used in our analysis for healthy, merged and insolvent companies.

Table 2: Descriptive statistics of variables/ratios						
	Healthy		Merged		Insolvent	
Variable /ratios	**Mean**	**StDev**	**Mean**	**StDev**	**Mean**	**StDev**
TD_TA	.2116	.1084	.5249	.3259	.6263	.1603
TC_EX	3.148	7.578	2.376	2.076	1.084	.4610
TA_EP	3.148	7.578	2.376	2.076	1.084	.461
TR_WP	.1670	.8256	.0599	.06253	.02544	.0322
WP_OF	3.3233	4.2232	3.8221	4.0215	3.5877	2.2841
NP_OF	.0673	.5822	.1268	.5922	-.3788	.6056
NP_WP	.0898	.3752	-.0439	.2672	-.0774	.1287
TA_TR	476.42	2715.54	76.74	144.39	1238.65	2316.58
EX_EP	.6846	.3598	.7941	.4149	.6307	.1693
I_EP	.8353	.2906	.7563	.2331	.6341	.1660
NP_TA	.0325	.0745	-.0246	.1328	-.030	.0475
OC_TR	139.61	824.41	16.08	35.68	451.66	1021.57

Note: Summary Statistics for the variables (ratios) used in DA, LR and MLR models

Table 3: Pearson's Correlation Coefficients												
	TD_TA	TC_EX	TA_EP	R_WP	WP_OF	NP_OF	NP_WP	TA_R	EX_EP	I_EP	NP_TA	OC_R
TD_TA	1.00	-.394	-.147	1.00	.173	.006	-.074	.116	-.188	-.145	.019	.117
TC_EX	.394	1.00	-.461	-.099	.379	-.040	-.236	.076	.105	-.445	-172	.081
TA_EP	-.147	-.461	1.00	-.365	-.170	.016	.289	-.046	.053	.325	.019	-.047
TR_WP	-.056	-.099	-.365	1.00	-.061	.058	.338	-.035	-.245	-.091	.145	.034
WP_OF	.173	.379	-.170	-.061	1.00	-.380	-.132	-.023	-.099	-.276	-.145	.016
NP_OF	006	-.040	-.040	.058	.058	1.00	.192	-.016	-.150	.039	.321	.023
NP_WP	-.074	-.236	.289	.338	-.132	.192	1.00	-.026	-.192	.076	.435	.028
TA_TR	.116	.076	-.046	-.035	-.023	-.016	-.026	1.00	-.013	-.073	-.040	.989
EX_EP	-.188	.105	.053	-.245	-.099	-.150	-.192	-.013	1.00	.303	-.456	.006
I_EP	-.145	-.445	.325	-.091	-.276	.039	.076	-.073	.303	1.00	.112	-.070
NP_TA	.019	-.172	.019	.145	-.145	.321	.435	-.040	-.456	.112	1.00	.045
OC_TR	.117	.081	-.047	-.034	-.016	-.023	-.028	.989	-.006	-.070	-.045	1.00

Note: Pearson's correlation coefficients for the variables (ratios) used in our analysis

Discriminant, Logistic, Multinomial

Case 1a (insolvent vs healthy companies): i) DA was implemented between insolvent and healthy cases using the stepwise method variable selection. In the final step, five variables were selected in the model, the others were insignificant. The score for insolvent companies is given by

$$z_1 = -25.57 - 54.91\ TD\_TA + 4.17\ TC\_EX + 5.54\ EX\_EP + 10.25\ I\_EP - 13.29\ NP\_TA$$

and for healthy companies by

$$z_2 = -13.91 + 4.73\ TD\_TA + 11.35\ TC\_EX + 1.03\ EX\_EP + 16.65\ I\_EP - 9.77\ NP\_TA$$

Each company is classified depending on the group with the highest score. More specifically, a company is classified into group 1 (insolvent) if $z_1 > z_2$, or otherwise into group 2 (healthy).

ii) Stepwise DA 100% correctly classifies all insolvent companies and 98.6% of the healthy ones.

iii) We implemented a LR analysis between insolvent and healthy companies. The forward stepwise method selected only three variables. LR correctly classifies 77.8% of all insolvent companies and 99.5 % of the healthy ones. The coefficients under LR are

$$Y_i = 14.94 - 29.23\ TD\_TA - 1.10\ TR\_WP + 7.4\ NP\_WP$$

All other coefficients were insignificant.

Case 1b: All the variables are entered in the model. i) DA gives excellent results, 100% correctly classifying all insolvent companies and 99.5 % of the healthy ones. ii) LR correctly classifies all insolvent companies and 98.6 % of the healthy ones. Table 4 illustrates detailed results on the classification under DA and LR methods.

Table 4a: Classification Based on Stepwise Method				
	Stepwise DA		Stepwise LR	
	Insolvent	Healthy	Insolvent	Healthy
Insolvent	9 (100%)	0 (0%)	7 (77.8%)	2 (22.8%)
Healthy	3 (1.4%)	214 (98.6%)	0 (0.5%)	216 (99.5%)
Table 4b: Classification Based on Entire Set of Variables				
	DA		LR	
	Insolvent	Healthy	Insolvent	Healthy
Insolvent	9 (100%)	0 (0%)	9 (100%)	0 (0%)
Healthy	1 (0.5%)	216 (99.5%)	0 (0%)	216 (100%)

Note: Classification results for insolvent and healthy companies based on stepwise DA and LR, and results by using the entire set of variables.

Case 2 (merged vs healthy companies): DA and LR were implemented for merged and healthy companies. In the final step, the stepwise DA for merged and healthy companies has included the same 5 variables included in the stepwise DA for insolvent and healthy companies. For merged companies the score function is

$$z_1 = -17.44 + 30.4\ TD\_TA + 4.99\ TC\_EX + 5.36\ EX\_EP + 11.09\ I\_EP - 17.44\ NP\_TA$$

and for healthy companies is given by

$$z_2 = -13.33 - 0.21\ TD\_TA + 11.53\ TC\_EX + 1.01\ EX\_EP + 16.27\ I\_EP + 11.25\ NP\_TA$$

Table 5 presents classification results of merged and healthy companies. For stepwise DA, 3 out of 14 merged companies classified as healthy and 6 healthy cases classified as merged ones. When the entire set of variables was used we obtained the same classification results as obtained with stepwise method.

Table 5: Classification Results		
Discriminant Analysis		
	Merged	Healthy
Merged	11 (78.6%)	3 (21.4%)
Healthy	6 (2.8%)	211 (97.2%)
Stepwise Logistic Regression		
	Merged	Healthy
Merged	10 (71.4%)	4 (28.6%)
Healthy	1 (0.5%)	216 (99.5%)

Note: Classification results for merged and healthy companies based on DA and LR models.

Case 3 (insolvent vs merged companies): DA and LR were applied for insolvent and merged companies. The following Table 6 presents DA and LR classified results based on the entire number of variables. Stepwise LR failed to give us reliable classification results, due to the small number of cases in each group.

Table 6: Classification Results		
Discriminant Analysis		
	Insolvent	Merged
Insolvent	9 (100%)	0(0%)
Merged	1 (7.1%)	13 (97.2%)
Logistic Regression		
	Insolvent	Merged
Insolvent	9 (100%)	0 (0%)
Merged	0 (0%)	14 (92.9%)

Note: Classification results based on DA and LR using the entire set of variables.

Case 4a (all groups of companies): DA and MLR were applied for insolvent, merged and healthy companies. Results of the overall classification give us an indication of the financial position and the trend of merged companies. First, we applied MLR method with the entire number of variables. For MLR, the likelihood ratio test indicates that 4 variables are significant, at 0.01 level of significance. Applying MLR with the 4 selected variables, we obtain the estimated regression coefficients in the two equations

$$z_{2i} = -3.8 + 14.3\ TD\_TA - 1.45\ TC\_EX - 4.12\ I\_EP$$

and

$$z_{3i} = -2.9 + 13.6\ TD\_TA - 2.6\ TC\_EX - 2.37\ I\_EP,$$

The overall classification for stepwise DA and selected MLR is illustrated in Table 7a.

Case 4b: The overall classification based on DA and MLR and using the entire set of variables (see Table 7b), provide slightly different overall classification results with stepwise and selected MLR especially for insolvent and merged companies.

To obtain a better insight on the future of merged companies we investigated them case by case and observed that actually merged companies that were classified as insolvent, were affiliated companies, which carried bad risks or they were in financial trouble and the Greek government forced the parent company to absorb them**.**

Case 5a (per year analysis): During the implementation of the above-described techniques data from 31 healthy companies have been used for 7 consecutive years. The question was that, if a trend appeared in one of the first years of the operation of a company, could it be carried on

for the next years resulting to an overestimate or underestimate of our models. Because of this we decided to apply all previously mentioned techniques per year. Table 8 presents analytical results for insolvent and healthy companies for each individual year by using the entire set of variables and variables selected by the stepwise method. Insolvencies appeared only in years 1996, 1997, 1998 and 2000.

Case 5b: DA and MLR were applied for individual years. DA was implemented with the entire set of variables and with variables selected with the stepwise method. MLR first implemented with the entire set of variables. Then, we implemented the MLR again with selected variables based on likelihood test, at significant level of 0.01.

Table 9 presents analytical results for insolvent merged and healthy companies for each individual year. Simultaneous insolvencies and mergers appeared only in years 1996, 1997, 1998. From a perspective of supervisory authority, potential insolvencies must be detected early enough to give the opportunity to regulators to take action, protecting consumers and to retain stability in the insurance industry.

Table 7a: Classification Results Based on Stepwise/Selected Method						
	Stepwise DA			Selected MLR		
	Insolvent	Merged	Healthy	Insolvent	Merged	Healthy
Insolvent	6(66.7%)	3 (33.3%)	0 (0%)	3 (33.3 %)	3 (33.3 %)	3 (33.3 %)
Merged	6(42.9%)	4 (28.6%)	4 (28.6%)	3 (21.4%)	2 (14.3%)	9 (64.3%)
Healthy	0 (0%)	11 (5.1%)	206(94.9%)	0 (0%)	2 (2.9%)	15 (91.7%)
Table 7b: Classification Results Based on the Entire Set of Variables						
	DA			MLR		
	Insolvent	Merged	Healthy	Insolvent	Merged	Healthy
Insolvent	6 (66.7%)	3 (33.3%)	0 (0%)	8 (88.9%)	0 (0%)	1 (11.1 %)
Merged	3 (21.4%)	8 (57.1%)	3 (21.4%)	0 (0%)	11(78.6%)	3 (21.4%)
Healthy	0 (0%)	7 (3.2%)	210(96.8%)	0 (0%)	1 (0.5%)	216 (99.5%)

Note: Classification results for insolvent, merged and healthy companies based on stepwise DA and selected MLR models and classification results for insolvent, merged and healthy companies based on DA and MLR models with entire data set.

Table 8a: Classification Results for Healthy and Insolvent Companies for Individual Years								
	1996		1997		1998		2000	
Discriminant Analysis with the Entire Set of Variables								
	Insolvent	Healthy	Insolvent	Healthy	Insolvent	Healthy	Insolvent	Healthy
Insolvent	4 (100%)	0 (0%)	1(100%)	0 (0%)	2(100%)	0 (0%)	2(100%)	0 (0%)
Healthy	0 (0%)	31(100%)	0 (0%)	31(100%)	0 (0%)	31 (100%)	0 (0%)	31(100%)
Logistic Regression with the Entire Set of variables								
	Insolvent	Healthy	Insolvent	Healthy	Insolvent	Healthy	Insolvent	Healthy
Insolvent	4 (100%)	0 (0%)	1(100%)	0 (0%)	2(100%)	0 (0%)	2(100%)	0 (0%)
Healthy	0 (0%)	31(100%)	0 (0%)	31 (100%)	0 (0%)	31(100%)	0 (0%)	31(100%)
Table 8b: Classification Results for Healthy and Insolvent Companies for Individual Years								
	1996		1997		1998		2000	
Stepwise Discriminant Analysis								
	Insolvent	Healthy	Insolvent	Healthy	Insolvent	Healthy	Insolvent	Healthy
Insolvent	4 (100%)	0 (0%)	1(100%)	0 (0%)	2(100%)	0 (0%)	2(100%)	0 (0%)
Healthy	0 (0%)	31(100%)	0 (0%)	31 (100%)	0 (0%)	31 (100%)	0 (0%)	31(100%)
Stepwise Logistic Regression								
	Insolvent	Healthy	Insolvent	Healthy	Insolvent	Healthy	Insolvent	Healthy
Insolvent	4 (100%)	0 (0%)	1(100%)	0 (0%)	2(100%)	0 (0%)	2(100%)	0 (0%)
Healthy	0 (0%)	31(100%)	1 (3.2%)	30(96.8%)	2 (6.5%)	29(93.5%)	2 (6.5%)	29(93.5%)

Note: Classification results for insolvent and healthy companies for individual years, based on stepwise DA and LR models and on the entire set of variables, respectively.

Table 9: Classification Results						
Year 1996	DA with all variables			MLR with all variables		
	Insolvent	Merged	Healthy	Insolvent	Merged	Healthy
Insolvent	4 (100%)	0 (0%)	0 (0%)	4 (100%)	0 (0%)	0 (0%)
Merged	0 (0%)	5 (100%)	0 (0%)	0 (0%)	5 (100%)	0 (0%)
Healthy	0 (0%)	1 (3.2%)	30 (96.8%)	0 (0%)	0 (0%)	31 (100%)
	Stepwise DA, (TD_TA, TA_EP, NP_OF)			Selected MLR, TD_TA, WP_OF, I_EP)		
	Insolvent	Merged	Healthy	Insolvent	Merged	Healthy
Insolvent	3 (75%)	1 (25%)	0 (0%)	2 (50%)	2 (50%)	0 (0%)
Merged	1(20%)	3 (60%)	1 (20%)	1 (20%)	1 (20%)	3 (60%)
Healthy	1 (3.2%)	1 (3.2%)	29 (93.5%)	0 (0%)	0 (0%)	29 (93.5%)
Year 1997	DA with all variables			MLR with all variables		
	Insolvent	Merged	Healthy	Insolvent	Merged	Healthy
Insolvent	1 (100%)	0 (0%)	0 (0%)	1 (100%)	0 (0%)	0 (0%)
Merged	1 (50%)	1 (50%)	0 (0%)	0 (0%)	2 (100%)	0 (0%)
Healthy	0 (0%)	1 (3.2%)	30 (96.8%)	0 (0%)	0 (0%)	31 (100%)
	Stepwise DA, (TD_TA)			Selected MLR, (TD_TA)		
Insolvent	1 (100%)	0 (0%)	0 (0%)	0 (0%)	1 (100%)	0 (0%)
Merged	1 (50%)	1 (50%)	0 (0%)	0 (0%)	2 (100%)	0 (0%)
Healthy	0 (0%)	1 (3.2%)	30 (96.8%)	0 (0%)	0 (0%)	31 (100%)
Year 1998	DA with all variables			MLR with all variables		
	Insolvent	Merged	Healthy	Insolvent	Merged	Healthy
Insolvent	2 (100%)	0 (0%)	0 (0%)	2 (100%)	0 (0%)	0 (0%)
Merged	0 (0%)	2 (66.6%)	1 (33.3%)	0 (0%)	3 (100%)	0 (0%)
Healthy	1 (3.2%)	0 (0%)	30 (96.8%)	0 (0%)	0 (0%)	31 (100%)
	Stepwise DA, (TD_TA, EX_EP)			Selected MLR (None)		
Insolvent	2 (100%)	0 (0%)	0 (0%)	-	-	-
Merged	1 (33.3%)	1 (33.3%)	1 (33.3%)	-	-	-
Healthy	2 (6.5%)	0 (0%)	29 (93.5%)	-	-	-

Note: Classification results for insolvent, merged and healthy companies for individuals years, based on DA and MLR models with all variables, as well as with variables selected with stepwise method (within the brackets are the variables selected in each stepwise model).

4.1 Cross-validation and reliability

For testing the predictability of our model, we split our data set to two subsets. A large data set (n=193), which includes financial characteristics for 186 cases of healthy companies that operated during the years 1996-2001 and 7 insolvent companies and a small data set (n=33) that includes financial characteristics for 2 insolvent companies and the 31 cases of solvent companies that operated in the year 2002. So the large data set was treated as test data and the small data set was treated as a new data set (cross-validation technique).

DA and LR for insolvent and healthy companies for the large data set were applied. The stepwise DA for insolvent and healthy companies, in the final step, has included the same five variables included in the stepwise DA for insolvent and healthy companies. For insolvent companies the score function is

$$z1 = -26.704 + 57.492\ TD\_TA + 3.556\ TC\_EX + 7.956\ EX\_EP + 9.312\ I\_EP - 14.204\ NP\_TA$$

and for healthy companies is given by

$$z2 = -14.653 + 3.598\ TD\_TA + 12.070\ TC\_EX + 1.658\ EX\_EP + 17.860\ I\_EP - 9.698\ NP\_TA$$

Then, the above two-score function applied to the small data set. Table 10 presents classification results of insolvent and healthy companies by implementing the DA and LR models by using the large data set. Stepwise DA in the final step, 100% correctly classifies insolvent companies and 99.5 % the healthy ones. When we applied DA to the small set we obtained 100% overall classification for insolvent and

healthy companies. Stepwise LR applied to the large data set failed to provide us with significant variables in order to test the predictability of the LR model for the small data set. When the large data set with the entire set of variables was used, the LR provided us with 100% overall classification.

In order to double check the predictability of our model, we applied the above two score function to some companies (healthy) that initially were not in our sample of the 31 healthy companies. These companies entered the Greek market later than the year 1996 and remained healthy until the year 2003. Stepwise DA 100% correct classified these companies.

Table 10a: Classification based the 1st set of Data

	Stepwise DA		Stepwise LR	
	Insolvent	Healthy	Insolvent	Healthy
Insolvent	7 (100%)	0 (0%)	7 (100%)	0 (0%)
Healthy	1 (0.5%)	185 (99.5%)	0 (0%)	186 (100%)

Table 10b: Classification based on the 2nd set of Data

	Stepwise DA		Stepwise LR	
	Insolvent	Healthy	Insolvent	Healthy
Insolvent	2 (100%)	0 (0%)	-	-
Healthy	0 (0%)	31 (100%)	-	-

Note: Classification results for Insolvent and healthy companies based on DA and LR, based on the large data set and predicted classification results based on the small data set.

An additional investigation has been made (getting information based on personal communication with insurance industry managers) confirming the reliability of our results, i.e., besides the 9 companies that went bankrupt 3 more companies had financial problems, but probably not big enough to go bankrupt. More specifically, one of the companies changed its brand name while another one started an excessive advertising campaign for marketing reasons and for recuperating its business profile. We have also been informed that these companies have been subject to either formal or informal rehabilitative activity by the Regulatory Authority.

Also, merged companies classified as healthy ones, were those that were absorbed by the parent company for management reasons (lower cost of operation, tax purposes etc.). Some of the merged companies that were classified as insolvent had financial problems and have been absorbed by their parent company or by other larger companies.

4.2 Stepwise Regression Analysis

In computer packages stepwise linear regression is an automatic search procedure for selecting which variables to include in a regression model. The forward stepwise regression is most widely used of the automatic search methods. This search method develops a sequence of regression, at each step adding or deleting an X variable. The procedure ends with the identification of a single regression model as "best". For more details the reader may refer to Neter et al. (1994), or any other book on linear regression models.

In the following analysis, we apply regression techniques that may justify the results of the previous section. Harrington and Nelson (1986) have also applied similar techniques to identify insurers with ratios that are substantially higher than those of insurers with similar characteristics.

Regression techniques may be used to estimate the relationship between written premium to own funds ratios (WP_OF) of a company and other characteristics (ratios) as illustrated in Table 2. If such a relationship exists, it can be used to identify insurance companies that deviate substantially from this estimated relationship. These companies may be subjects of careful supervision from the regulatory authorities. The estimated regression line can be considered as the industry equation (norm).

An advantage of this regression approach is that, data of insolvent companies are not needed for the estimation of the required parameters. A lot of preliminary work (stepwise analysis, analysis of variance for the importance of regression coefficients, etc.) has been done to determine what variables to include in the regression model.

1st Regression model: In the first model we consider the ratio WP_OF as the dependent variable and all the rest variables defined in Table 2, as the independent variables. The forward stepwise regression identifies that the TC_EX, NP_OF, EX_EP as the "`best" subset of X variables. Thus, our 1st model is

$$WP\_OF = f(TC\_EX, NP\_OF, EX\_EP)$$

and the regression coefficients are given in Table 11.

Table 11: Regression Coefficients

	Value	Std. Error	t value	Pr(> |t|)
Intercept	1.2455	0.7018	1.7747	0.0772
TC_EX	4.1078	0.5798	7.0842	0.0000
NP_OF	-2.7876	0.3846	-7.2478	0.0000
EX_EP	-2.3012	0.6342	-3.6283	0.0003

Note: Parameter Estimation with WP_OF as a dependent variable and TC_EX, NP_OF , EX_EP, as the selected independent variables (ratios), $R^2 = 0.3152$, $F = 36.22$.

Table 11 indicates that the mean of WP_OF is expected to increase by 4.1078 if we increase the value of TC_EX, by 1, holding the rest of the independent variables constant, and that mean is expected to decrease by 2.7876 if we increase the value of NP_OF by 1. Similarly the mean WP_OF is expected to decrease by 2.3012 if we increase the value of EX_EP, by 1, keeping the rest of independent variables constant.

2nd Regression model: In the second model we consider the TR_WP as the dependent variable and the rest of the variables defined in Table 2, as the independent variables. The forward stepwise regression identifies that the TC_EX, TA_EP, NP_WP, EX_EP, NP_TA as the "`best" subset of X variables. Thus, our 2nd model

TR_WP = f (TC_EX, TA_EP, NP_WP, EX_EP, NP_TA)

and the regression coefficients are given in Table 12. Table 12 indicates, that the mean of TR_WP is expected to decrease by 0.5771 if we increase the value of TC_EX, by 1, holding the rest of the independent variables constant, that mean is expected to decrease by 0.0683 if we increase the value of TA_EP by 1, and that mean is expected to increase by 1.0792 if we increase the value of NP_WP by 1. Similarly the mean of R_WP is expected to decrease by 0.3760 if we increase the value of EX_EP, by 1, and that mean is expected to decrease by 1.8559 if we increase the value of NP_TA by 1, keeping the rest of the independent variables constant.

Table 12: Regression Coefficients

	Value	Std. Error	t value	Pr(> |t|)
Intercept	1.1307	0.1488	7.5968	0.0000
TC_EX	-0.5771	0.1139	-5.0660	0.0000
TA_EP	-0.0683	0.0062	-10.952	0.0000
NP_WP	1.0792	0.1228	8.7867	0.0000
EX_EP	-0.3760	0.1210	-3.1065	0.0021
NP_TA	-1.8559	0.5941	-3.1239	0.0020

Note: Parameter Estimation with TR_WP as a dependent variable and TC_EX, TA_EP, NP_WP , EX_EP NP_TA as the selected independent variables, $R^2 = 0.4421$, F = 37.0.

3rd Regression model: In the third model we consider the I_TA as the dependent variable and all the rest of the variables defined in Table 2, as the independent variables. The forward stepwise regression identifies that the TC_EX, EX_EP, I_EP as the "best" subset of X variables. Thus, our 3rd model is

I_TA=f (TC_EX, EX_EP, I_EP)

and the regression coefficients are given in Table 13.

Table 13: Regression Coefficients

	Value	Std. Error	t value	Pr(> |t|)
Intercept	0.0573	0.0495	1.1587	0.2478
TC_EX	0.2159	0.0289	7.4580	0.0000
EX_EP	-0.1361	0.0294	-4.6252	0.0000
I_EP	0.0964	0.0409	2.3595	0.0191

Note: Parameter Estimation with I_TA as a dependent variable and TC_EX, EX_EP, I_EP as the selected independent variables, $R^2 = 0.2261$, F = 22.99.

Table 13 indicates that the mean I_TA is expected to increase by 0.2159 if we increase the value of TC_EX, by 1, holding the rest of the independent variables constant and that mean is expected to decrease by 0.1361 if we increase the value of EX_EP by 1, and that mean is expected to increase by 0.0964 if we increase the value of I_EP by 1, keeping the rest of independent variables constant. Of course more detailed regression analysis could be implemented with more detailed data, taking into account endogenous and exogenous factors, as well as the peculiarity of each branch of the insurance industry.

5 DISCUSSION & CONCLUDING REMARKS

This article can be considered as a guide for solvency supervision and for predicting financial distress of insurance companies. It also presents an overview of solvency supervision and insolvency prediction including the effects of solvency position of insurance companies, the objectives for solvency regulations and the role of the government for protecting the public against insolvency.

Methods implemented in this paper have been extensively applied in the insurance-actuarial literature in the past and the variables that were selected are those that were available in the Bulletin of the General Secretariat of Trade, the Direction of Insurance Companies and were appropriate for our analysis. Stepwise DA and LR were applied with data for each individual year, from 1996 through 2002, for 31 healthy companies and companies that have been merged or failed during those years. DA and LR were applied by using the entire set of variables. Surprisingly, in most cases, the use of the entire set of variables in the DA and LR model provided higher classification rates than those obtained by using stepwise analysis. This is due to the classification criterion (posterior probability) applied, conditional on the vector of discriminating variables.

We have applied the above-mentioned techniques with different sets of data. DA and LR and MLR were applied with data for each individual year, from 1996 through 2002, for 31 healthy companies and companies that have been merged or failed during those years. The models applied also with data for all years together. In most cases we obtained similar results by using the entire data (from 1996-

2006 together) and data for individual years. In few cases, due to the very small data set, especially for insolvent companies, LR and MLR failed to give reliable results. The predictability of our models was checked by splitting the data set into two subsets, the large data set that was treated as test data, and the small data set that was treated as a new data set (cross-validation technique).

In order to double check the predictability of our model we applied the above techniques to some companies (healthy) that initially were not in our sample of the 31 healthy companies. Three Regression models were applied to estimate the relationship between some important ratios with other characteristics. The estimated regression lines can be considered as industry equations (norms) and can be used to identify insurance companies that deviate substantially from this estimated relationship. The industry regression norm can be useful for solvency surveillance by the regulators, and can be valuable to consumers, sales personnel, and managers that are interested in evaluating the financial strength of an insurance company. Of course more studies must be undertaken and the same methodology should be applied to a more detailed data and more financial characteristics have to be used, taking into account the peculiarity of the insurance market of each country.

Solvency position needs further investigation and it does not depend only on endogenous factors (good management, good estimation of technical reserves, etc.), but also on exogenous factors as well (rates of return, unemployment rate etc.). For example, the level of long-term interest rates may be related to the rate of insolvencies, since interest earnings are a significant source of revenue for insurance companies. Today the low rates of interest indicate an unfavourable investment environment for insurers, especially for life-healthy ones. Further studies must be conducted in different lines of business for life and non-life insurance, separately, taking into account the risk based capital and other important characteristics of the insurance industry.

Based on our results and previous studies, we have concluded that there is not a single methodology adequate for predicting insurer insolvency. Techniques should be focused not only on the values of balance sheets, but on the operation of the insurance companies, the management, the regulatory ratings as well as the public opinion. Legislation rules must be stricter in order to avoid public harm, which usually means taking insolvent insurer out of the market place promptly by withdrawing its license.

Facing a new era of risks such as catastrophes and terrorism, risk undertaking is not an easy task for the insurance market, since not much data experience is available, new business rules are applied due to globalisation of the economy and consequently of the insurance industry as well. The EC insurance industry is now a subject to international competition in areas as wholesales insurance and reinsurance. Insurance companies have expanded beyond their national markets and increased integration of financial service with banks moving into insurance business.

Countries which undergo a transition period due to the reform of their insurance market regulatory system, could face the same problem Greece faced in the middle 70's and early 80's, i.e. lack of strict legislation, etc. An issue, which is very serious, and needs to be considered by the Supervisory Authority is fraud against the public and consequently against the Government: Cooking the books has some consequences. At first, the insurer can avoid regulatory action. As the problem becomes bigger problems in the balance sheet become more obvious. Cooking the books can lead to overcooking and finally the company can burn itself in a worse way than just presenting its distressed situation in the first place.

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