Insurance solvency in Iran

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Abstract

Solvency level of an insurer influences financial situation of the stakeholders. All stakeholders related to an insurer have a concern about its solvency status. The models of bankruptcy prediction particularly Altman's Z-Score models represent an intuitive and interpretable score of bankruptcy. The main variables in Merton’s models for bankruptcy are unobservable. In this article, we instead develop a seminal multiple regression model for estimating the more objective solvency ratio of insurance institutions. The model including risk-reflecting independent variables is estimated using panel data of a sample of Iranian insurers. Based on relevant tests, the Individual Effects Random Effects model looks like a reliable model for solvency ratio of Iranian insurers. Based on results, a relationship between the size of insurers and their solvency ratio is significantly rejected. Additional capital does not surprisingly make a relationship with the higher levels of solvency ratio. There exists a paradox between Capital Adequacy and Provisions Adequacy of an insurer. However, history is significantly related to the solvency ratio implying that the newly-established companies bring a relatively large amount of capital without taking over considerable risks in the first years of operation and that the growth rate of risks is higher than growth rate of capitalization in Iranian insurers over time. The variable of being listed in the Tehran Stock Exchange is also positively related to the dependent variable meaning that the second supervisor really works and is efficient. Of course, only the insurers obtaining eligibility requirements are listed. So, the positive relationship may imply that only solvent insurers are listed. More stable insurers are more solvent. Our results indicate that stability leads to solvency or inversely. Interest rate, as a macroeconomic factor, positively contributes to strongly explain the solvency of insurers. Investment profits compared to underwriting profits are considerable and sometimes exceeds in insurance industry of Iran. The main part of investments of the insurers is as deposits. This may be the reason for positive relationship between interest rate and solvency. Some detailed policy implications are presented in the article based on our findings.

Introduction

“Insurance should rightly be perceived not only as a protection and risk management mechanism (see Zimbidis et al., 2007, Pantelous et al. 2014), which pays out when a catastrophe occurs, but more as a partnership that allows individuals and businesses to spread their wings and go where they might otherwise not have dared to go” (Grant, 2012). It is widely known that the insurance industry plays a crucial role in and it is of a great importance to domestic and global economies.

Thus, its role within the financial system expands and changes in response to a wide range of social, financial and economic developments. The key benchmark of an insurance company is its solvency, and it has a clear impact on the financial market and the whole economy. From social point of view, it is very important that insurance companies remain solvent in order to ensure the smooth functioning of insurance markets and the protection of policyholders, see Godinez-Olivares et al. (2014) (and references therein) for the public pension system. The maintenance of solvency position, adequate levels of capital and reserves for insurance companies plays a large part in achieving the objectives of supervisory frameworks. Nowadays, solvency value and its prediction are of the most important variables and topics for insurers. It is a key component in assessing financial stability of an insurer (Dean, 2011). Moreover, as David Snyder (2014), associate general counsel of the Washington-based American Insurance Assn, states "drafting Solvency II began well before the financial crisis, but the crisis helped assure its adoption and may lead to strengthen regulation".

Financial crises have been pervasive for many years. Bordo et al. (2001) find that their frequency in recent decades has been double that of the Bretton Woods Period (1945-1971) and the Gold Standard Era (1880-1993), comparable only to the period during the Great Depression. Nevertheless, the financial crisis that started in the summer of 2007 came as a great surprise to most people. It resulted in the threat of total collapse of large financial institutions, the bailout of banks by national governments, and downturns in stock markets around the world. Some of the world's best-known financial institutions including insurers collapsed or were nationalized, while many others survived only with massive state support.

Since the initial Solvency I Directive was introduced in 1973, more elaborate risk management systems developed. The Solvency II Directive aims to review the prudential regime for insurance and reinsurance undertakings in the European Union. As a first step, the Solvency II Directive was adopted by the Council of the European Union and the European Parliament in November 2009. In the next step it will be implemented soon. Due to continuing uncertainties surrounding insurance companies and risks inherent in their operation and hence increasing insolvency risk, establishing risk management systems including solvency systems and other similar systems in different countries seem more necessary and on-time than ever.

Because of the risks surrounding insurance industry, the overall success and continued sustenance of an insurer depends largely on the solvency status of the insurer. In solvency systems, such as the Solvency II etc, solvency status or level of an insurer is usually defined by solvency ratio of an insurer which is roughly defined as a ratio of available capital to required capital (risk). It shows how much an insurer is able to cover its all risks by capital. A press release issued by the European Union stated that under Solvency II "insurers must have available resources sufficient to cover a Solvency Capital Requirement (SCR) based on a Value at Risk measure calibrated to a 99.5% confidence level over a 1-year time horizon" (Hayes, 2009). Due to the nature of activities in risk-taking by an insurer, as a type of large service providers, all its stakeholders including shareholders, policyholders, managers, regulator and debtors are concerned about its solvency status.

According to the Directive No. 69 approved by Insurance High Council of Iran, solvency ratio value of an Iranian insurer must be annually/biannually calculated and released by insurer. However applying a multiple regression model which will be introduced in this article, stakeholders are able to know it earlier and to predict it for several future years (e.g. to be included in the strategic plan of the insurer[1]). They may not have access to enough data and complex knowledge that solvency systems need. So, a rather direct regression model than solvency systems is more desirable. Moreover, it is important for regulators to take early action to prevent insolvency or financial distress of insurers, to stabilise and eventually control (or manage) it (Pantelous and Papageorgiou, 2013, Pantelous and Yang, 2014). Managers of insurer, policyholders, creditors, rating institutes, lenders and potential investors are interested in predicting solvency ratio for the purposes of control or investment. In order to control future solvency status, using the results of this regression model, stakeholders are able to know which factors have the highest meaningful relationship with solvency value and to predict it.

The regression model provides useful information about how and why the solvency of an insurer is decreasing or increasing for relevant stakeholders. Using this meaningful risk-reflecting model, stakeholders are able to figure out how much factors of different levels (firm, market and macro factors) affect the solvency of insurers in comparison. Further, stakeholders are able to predict how much in the form of solvency ratio an insurer at risk is.

Although there are lots of work around solvency and its capital requirements, our statistical regression modelling of solvency ratio is a seminal and original work. In fact, to our exhaustive searching and to the best of our knowledge, the solvency ratio has not yet been modelled by the regression analysis. With this regard, the article proposes a seminal and original idea and model as potential outcome. The reasons stem from the fact that the solvency ratio is not common in all industries and that the solvency concept and hence its related ratio do not analogously have a long term history. Regression modelling solvency ratio and its relationships with independent variables can be considered as a new and a state-of-the-art approach to the bankruptcy modelling in insurance industry. Of this point of view, the article has an innovative and original idea for contribution.

The article is structured as following: First, a review of the literature is given. The review starts from bankruptcy prediction models, since solvency is closely related to the bankruptcy. In the next section, the problem of interest is clarified. The basic idea of the article is then presented in the section of motivation. Research questions and objectives of the research are articulated in the next section. The methodology of research and the data needed is then explained. A multiple regression for modelling the solvency ratio using a sample of panel data corresponding Iranian insurers is specified. For better understanding of insurance industry in Iran, we then present an overview of the industry providing the most important statistical data. For justification of insurance solvency modelling we give the relevant theoretical background in the next section followed by a short description of solvency system in Iran. The next section presents the process of model estimation and validation. The results of estimated and validated model are presented in the next section. We then try to interpret the results and findings. The last section concludes based on the results and the interpretations. Some policy implications extracted from the results are suggested.

[1] With the introduction of the Own Risk Solvency Assessment (ORSA) under Pillar 2 of Solvency II for an example, regulators require insurance companies to prove their ability to meet the regulatory margin requirements not only on the date of inventory but also prospectively, under the horizons of their strategic plans. Accordingly, an insurer must be able to project the main characteristics of its balance sheet over a period of 3 to 5 years depending on the duration of the strategic plan in addition to accounting for new business plans written over the period.

Literature review

Bankruptcy risk can be defined as "the possibility that a company will be unable to meet its debt obligations. Bankruptcy risk describes the likelihood that a firm will become insolvent because of its inability to service its debt". This definition is closely related to the definition of the insurance solvency by Quadrelli and Di Lorenzo (2013) which states that "a risk responsive capital measure calibrated to ensure that each insurer will be able to meet its obligations over the next 12 months with a probability of 99.5%".

The vast majority of the empirical research related to bankruptcy risk is concerned with developing models to predict bankrupt and non-bankrupt companies. The seminal works in this area are by Beaver (1966) who employed Univariate prediction models, Altman (1968, 1973, 1983 and 2006) who utilized Multivariate Discriminate Analysis (MDA) and Ohlson (1980) who developed a Conditional logistic regression (Logit) prediction model.

The so-called $\boldsymbol{Z}$-Score of Altman represents an overall index of corporate fiscal health. The range of the $\boldsymbol{Z}$-value for most corporations is between -4 and +8. Those in the middle are question marks that could go either way. The closer the firm gets to bankruptcy, the more accurate the $\boldsymbol{Z}$ value is as a predictor. However, the range of acceptable values is confusing. Users would perhaps, have preferred $\boldsymbol{Z}$-value set in fractions or percentages as these are more or less universal and better understood than the number range used. The $\boldsymbol{Z}$-score is a linear combination of five common financial ratios including "Working capital to Total assets" $\boldsymbol{X_1}$, "Retained earnings to Total assets" $\boldsymbol{X_2}$, "Earnings before Interest and Tax to Total assets" $\boldsymbol{X_3}$, "Market value of equity to Book value of total liabilities" $\boldsymbol{X_4}$ and "Sales to Total assets" $\boldsymbol{X_5}$ (with the estimated parameters by Altman (1968), the model is as $\boldsymbol{Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5}$).

Ohlsons' (1980) Logit bankruptcy prediction model (sometimes referred to as Ohlson's $\boldsymbol{O}$-score) allows for the estimation of the probability of bankruptcy conditional on the values of nine financial ratios. Ohlson (1980) raised questions about the MDA model, particularly regarding the restrictive statistical requirements (normality of predictors) imposed by the $\boldsymbol{Z}$-score model. In the Linear Probability Model (LPM) of Ohlson (1980), the dependent variable, $\boldsymbol{Y}$, which expresses the dichotomous $\boldsymbol{Y}$ as a linear function of the explanatory variable(s), takes 1 if the event occurs (say firm fails) and 0 if the event does not occur (say the firm does not fail). The variable $\boldsymbol{Y}$ is sometimes referred to as a dummy variable. Such the model is called LPM because the conditional expectation of $\boldsymbol{Y}$ given $\boldsymbol{X}$ can be interpreted as the conditional probability that the event will occur given $\boldsymbol{X}$. While Altman's $\boldsymbol{Z}$-Scores allow one to discriminate between those firms likely to encounter financial distress and those unlikely to experience distress, they cannot be interpreted as bankruptcy probabilities.

Kruschwitz and Löffler (2005) used a model of cash flow stochastic processes called weak autoregressive cash flows which is close to Ohlsons' model. They consider two types of unlevered and levered firms. Cash flows of the unlevered firm are weak autoregressive, i.e. noise terms are uncorrelated. If costs of capital are deterministic and cash flows are weak autoregressive, then costs of capital of unlevered firm are discount rates. Kruschwitz, Lodowicks and Löffler (2005) analyzed the impact of insolvency on the value of a firm under conditions of uncertainty. They obtain the rather surprising result that the possibility of a default does not affect the value of the firm at all as long as its financing policy is given. In the context of their analysis it is not necessary to specify explicitly either the default trigger or the financing policy. The result is illustrated for a binomial example with an autonomous financing policy.

Shumway (2001) proposed a discrete time hazard model to predict a firm's bankruptcy using both accounting and market variables. The variables used to give an early warning of bankruptcy are mostly traditional accounting ratios from financial statements. He, however, finds that half of the accounting variables used by Altman (1968) are statistically unrelated to bankruptcy probability. Instead, he argues some market variables such as firm size, past stock returns, and idiosyncratic returns variability are all strongly related to bankruptcy risk.

After the establishment of Altman's ***Z***-score models, abundant studies have done further research on the bankruptcy. Beneda (2007) investigates after-market returns and incidence of bankruptcies and distress relative to performance and distress indicators for new public companies. The study includes firms that had an initial public offering (IPO) during the period 1995-2002. Performance measurements include after-market returns, number of bankruptcies, and number of "distressed" firms. The results of the study indicate that using Ohlson ratio, the market-to-book ratio, and underwriter quality as selection criteria may result in a portfolio of IPOs which performs above average. Das et al. (2009) provide compelling evidence that accounting metrics are important to providers of debt capital. Using a sample of 2,860 quarterly of Credit Default Swap (CDS) spreads available over the period 2001-2005 they find that a model of distress which is entirely composed of accounting-based metrics performs comparably, if not better, than market-based structural models of default. Furthermore, they find that both sources of information (accounting- and market-based) are complementary in pricing distress. These results support the notion that accounting metrics have direct value- or valuation-relevance to debt holders and holders of credit derivatives. Zhang and Nielson (2013) incorporated macroeconomic conditions and state-specific factors and achieved greater generalizability and predictive accuracy. Their findings support the argument that insolvency likelihood increases for insurers domiciled in states with stricter solvency supervision and/or states with less favourable insurance market conditions, and during soft markets; insolvency risk is negatively related to the slope of the yield curve. Their findings also imply that insurers respond efficiently to changes in such market factors as market return, inflation, and catastrophic losses.

In general, default is triggered by a firm's failure to meet its financial obligations. There are indeed two primary types of models that describe default processes in the literature: reduced-form models (accounting based) and structural models (market based). Reduced-form empirical models as some of them referred above do not consider the relation between default and firm value explicitly. Structural models use the evolution of a firm's structural variables, such as asset and debt values, to determine the timing of default. They relate the credit quality of a firm and the firm's economic and financial conditions. Merton's model (1974) based on Black and Scholes (1973) Option Pricing Theory is considered as the first structural model. In Merton's model, a firm defaults if, at the time of servicing the debt at debt maturity, its assets are below its outstanding debt. The core concept of the structural models, which originated from the seminal work of Merton (1974), is to treat a firm's equity and debt as contingent claims written on the firm's asset value. A second approach within the structural framework was introduced by Black and Cox (1976). In this approach default occurs when a firm's asset value falls below a certain threshold. In contrast to the Merton approach, default can occur at any time.

In Merton's model (1974), it is assumed that the asset value of the firm, $\boldsymbol{V}$, follows a Geometric Brownian Motion with drift equal to the risk-free rate, $\boldsymbol{r}$, and volatility $\boldsymbol{\sigma}$: $dV_t=V_t(rdt + \sigma dW_t)$, where $\boldsymbol{W}$ is a standard Brownian Motion. In this setup, the firm defaults when its asset value at maturity, $\boldsymbol{V_T}$, is equal to or less than the value of its debt at maturity, $\boldsymbol{D}$. Hence, the creditworthiness of a firm can be measured by the difference between the firm's asset value and the firm's liabilities at maturity that is the distance-to-default (***DD***). The smaller the ***DD*** the higher the default risk is. The expected distance-to-default, $\boldsymbol{d}$, for a firm given its current asset value, $\boldsymbol{V}$, and the face value of its debt, $\boldsymbol{D}$, maturing $\boldsymbol{T}$ periods ahead, is then given by: $d=log(V_T)-log(D)=log(V)+(r-\sigma^2/2)T+\sigma W_t-log(D)$. Following Crosbie (1999), it is useful to normalize the distance-to-default by the firm's volatility, $\boldsymbol{\sigma}$. Rearranging terms, we can define the normalized ***DD*** as: $DD=d/(\sigma\sqrt{T})-W_t/\sqrt{T}=(log(V/D)+(r-\sigma^2/2)T)/\sigma\sqrt{T}$. The normalized ***DD***, can be interpreted as the number of standard deviations a firm is from default, measured in terms of its asset volatility. The ***DD***, is derived under a risk-neutral measure that allows setting the drift of the asset value equal to the risk-free rate. Working with the risk neutral measure simplifies calculations since it eliminates the need to estimate the drift of the asset value.

As Chan-Lau et al. (2004) state, calculating the ***DD***, requires knowing the asset value and the asset volatility of the firm. These two variables are difficult to measure accurately. However, if the face value of debt, $\boldsymbol{D}$, and its maturity, $\boldsymbol{T}$, are known, the two unobserved variables can be calculated from the firm's equity value, $\boldsymbol{E_t}$, and its volatility, $\boldsymbol{\sigma_E}$. The latter two variables are observable and can be expressed as functions of the asset value and the asset volatility of the firm. Therefore, the asset value and asset volatility can be recovered from the equity value and equity volatility functions. Moody's ***KMV*** is one notable commercial application of the model for predicting corporate defaults (Crosbie, 1999). This model is used in financial industry. The model of Kealhofer et al. (1998, 2001) is also another application of the Merton's model. More recently, the International Monetary Fund (2011) reports that aggregated ***DD*** series computed for the US banking system did a good job in forecasting systemic extreme events and in detecting early turning points near systemic events in the last decade, even though these series were computed using historical equity information. A strength point of Merton's model is, as opposed to the accounting-based models discussed earlier, market prices are independent of a company's accounting policies. Market value should reflect book value plus future abnormal cash flow expectations under clean surplus accounting, and thus, expectations of future performance.

The model of Merton entails several other drawbacks and shortcomings. The contingent claims approach to modelling corporate default risk in the model entails mapping a distance to default to a probability of default in application. To accomplish this, the research community typically assumes a normal distribution. The authors question the practical relevancy of such research, since the contingent claims approach most commonly used in practice, Moody's ***KMV***, uses an empirical expected default frequency (EDF) for this purpose. Moreover, the ***DD*** model has several interpretations. Chan-Lau et al. (2004) use the model as a measure for bank vulnerability. Charito et al. (2008) call the model as a type of bankruptcy prediction and structural credit risk models. Čihák and Hesse (2008) use the model as a measure for financial stability of banks. The Contingent Claims Analysis (CCA) approach has been cited and reviewed by the Financial Stability Board (2009) as a tool to enhance systemic risk analysis and to identify systemically important financial institutions and help establish a regulatory framework that can cope with risk arising from systemic linkages. Also, Zambrana (2010) tries to use this as a measure for systemic risk. Also the underlying Black-Scholes model makes some strong assumptions: lending and borrowing can be done at a known constant risk-free interest rate; price follows a geometric Brownian motion. No transaction costs exist; no dividend is paid; it is possible to buy any fraction of a share; and no short selling restrictions are in place. Other potential problems with the Merton model itself are: it can be difficult to apply it to private firms, it does not distinguish debt in terms of seniority, collateral, covenants, or convertibility; and, as Jarrow and van Deventer (1999) point out, the model assumes debt structure to hold constant.

As Duan and Wang (2012) argue, estimation of the asset value and the asset volatility becomes a serious challenge simply because the asset values are not directly observed. It is easy to obtain the equity value of an exchange listed firm, but the same cannot be said about the asset value. A direct valuation of asset value is practically impossible, because a firm as a going concern presumably possesses intangible assets and their values are hard to determine. Adding together the market values of equity and debt to arrive at the market value of the firm makes sense conceptually, but the market value of debt is hard to come by because a typical firm will have a large portion of debt in some non-tradable forms. Thus, a hybrid approach of adding market capitalization (equity value) to the book value of liabilities became very popular in corporate finance literature. The papers using this market value proxy method to obtain firm value are too numerous to mention. By reducing the Merton's model, this vast literature define a measure as $\boldsymbol{Z \equiv (k+\mu)/\sigma}$, where $\boldsymbol{k}$ is equity capital as percent of assets, $\boldsymbol{\mu}$ is return as percent of assets and $\boldsymbol{\sigma}$ is standard deviation of $\boldsymbol{\mu}$, is a $\boldsymbol{Z}$-score measure for corporate bankruptcy or financial stability of firms[2]. The popularity of the this $\boldsymbol{Z}$-score stems from the fact that it has a clear negative relationship to the probability of a firms' insolvency, that is, the probability that the value of its assets becomes lower than the value of its debt. It can be interpreted as the number of standard deviations by which returns would have to fall from the mean to wipe out all equity in the institution. If one adopts the market value proxy method, estimating the two parameters ($\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$) becomes fairly straightforward. One can obtain a time series of, say, daily asset values by summing daily updated market capitalizations with quarterly updated book values of liabilities. With the time series in place, one can obtain the daily logarithmic asset returns and then compute the sample mean and standard deviation of the return as the estimates for $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$. This reduced form of the Merton's model was defined by Boyd and Runkle (1993) and was used by De Nicolo (2000), Brockman and Turtle (2003) and Eom et al. (2004), Čihák and Hesse (2008) and many others in the empirical credit risk literature. Roy (1952) shown that the probability that current losses would exceed capital is less than or equal to $\boldsymbol{1/Z^2}$, so that higher level of $\boldsymbol{Z}$ implies lower upper bound of insolvency probability. The $\boldsymbol{Z}$-score has been widely used as a measure of financial stability in banking industry. However, the quality of the market value proxy method is questionable. It has been argued in Wong and Choi (2009) that such a method will produce an upward biased estimate of the asset value. All in all, although the basis Merton's model (1974) is a

[2] This $\boldsymbol{Z}$-score here is quite different to the Altman $\boldsymbol{Z}$-score but both intend to define bankruptcy.

type of structural Option Theory-based model, it is eventually applied using balance sheet information in practice in the literature and thus is reduced to the empirical Altman's ***Z***-score. See for example, Ivičić et al. (2008).

Xu and Zhang (2009) investigate if bankruptcy of Japanese listed companies can be predicted using data from 1992 to 2005. They find that the traditional measures, such as Altman's ***Z***-score, Ohlson's ***O***-score and the option pricing theory-based distance-to-default, previously developed for the U.S. market, are also individually useful for the Japanese market. Moreover, the predictive power is substantially enhanced when these measures are combined.

Problem

The bankruptcy prediction became a popular research topic lately; however the models used for evaluating companies have remained almost unchanged. The Altman's ***Z*** formula as the most popular model works well provided the scores fall within the "in the tails". The closer the firm gets to bankruptcy, the more accurate the ***Z*** value is as a predictor. Users would perhaps, have preferred ***Z***-value set in fractions or percentages as these are more or less universal and better understood than the number range used. The Altman's model suffers also from other drawbacks. The bankruptcy model should only be used for predicting financial distress if the company being analysed is comparable to the firms in Altman's samples. Altman applied the MDA to a dataset of manufacturers. It is a known fact that financial enterprises were to varying degrees negatively affected by the crisis; so the financial industry is not the most interesting to examine (Altman, 2001).

A matched-pair sample design combined with a dichotomous classification test has been the standard. The variable data is then used to differentiate correctly bankrupt and non-bankrupt companies. The underlying problem with the dichotomous evaluation model is that bankruptcy can no longer be thought of as a dichotomous variable (Haber, 2005). The ***Z***- score, as an overall index defined by Altman takes a value between certain limits. In the Linear Probability Model (LPM) of bankruptcy, the dependent variable, ***Y*** takes 1 and 0. These dependent variables (indices) are intuitive, subjective and non-observable. The ***Z*** index as a proxy is an interpretable variable in its nature. The ***Z*** index, as a generic model, is also a measure of strategic performance (Chakravarthy, 1986), financial health (Ferrier et al., 2002) or a credit scoring system (Altman, 2002). Indeed, definition of bankruptcy is difficult and not the same in different countries (Haber, 2005). Altman (1968) and pretty much all papers that followed, selected variables without the benefit of the theoretical development of what a bankrupt company should look like. Necessarily, there needs to be a discussion of what bankruptcy is and what it means. Perhaps, one of the major inappropriate leaps made by previous research was equating bankruptcy with (lack of) liquidity and insolvency. Bankruptcy comprises two major types: liquidation and reorganization. Liquidity and insolvency would appear to be closely related; however bankruptcy is not synonymous with liquidity or with insolvency. Insolvency could lead to bankruptcy, but because a company has filed for bankruptcy does not mean that they are insolvent. Likewise, there is no requirement that the insolvent company file for bankruptcy. They may try to solve their financial problems without resorting to bankruptcy court. While models might predict a company is bankrupt when the company did not file, the model might be accurate in profiling the company despite the lack of a bankruptcy petition (Haber, 2005).

While some of the shortcomings (such as the lack of a precise definition for bankruptcy) of the accounting based Altman's ***Z***-score models hold also true in the case of the market based structural Merton's models, the latter suffer from several additional shortcomings. As stated above, the asset value and volatility are unknown and unobservable. The research community typically assumes a normal distribution for the variables. Also the underlying Black-Scholes model makes some strong assumptions. The ***DD*** model has several interpretations. It is difficult to apply the model to private firms. It does not distinguish debt in terms of seniority, collateral, covenants, or convertibility. Finally, the model assumes debt structure to hold constant. Finally, the structural Option Theory-based Merton's model is reduced to an accounting-based model in practice.

Among the problems mentioned above, in this article we would like to consider the most significant, i.e.: 1) applicability to insurance firms, 2) dichotomy, 3) intuition or subjectivity of ***Z***, 4) interpretability of ***Z***, 5) scale of measure, 6) normality and some other assumptions.

Motivation

In principle, a value of solvency ratio is a signal for insolvency or bankruptcy probability of an insurer[3]. In this article, we are interested in developing a seminal model for predicting the well-defined and more objective solvency ratio[4] which is based on The Theory of Solvency Regulation (Munch and Smallwood, 1981) and on more accurate and precise estimation methods of risks such as Value at Risk or Expected shortfall rather than bankruptcy indexed by ***Z***-scores. The ***Z***-score formulas of Altman and Merton are generic models applied to any type of firms. However, insurer solvency assessed by known systems such as the Solvency I, Solvency II, the US RBC, German Standard Model of GDV and BaFin, the SST, A. M. Best's model etc. is a specific variable in insurance industry which compresses many types of risk in a single ratio.

The problem of interest here is not a binary classification of bankrupt and non-bankrupt firms. Solvency instead is determined by the continued viability of the insurer and in turn by those risks it has taken. Solvency is a continuum. This research paper suggests that the bankruptcy concept of an insurer is objectively represented as a continuum, rather than dichotomy with a transparent interpretation by the solvency ratio. Adopting a Total Balance Sheet approach like in the Solvency II, we focus on those simple financial ratios such as Debt and Current ratios representing financial and liquidity risks as predictive variables that can be directly controlled by the insurer. The predictive variables are considered among those financial ratios to be a representative for a type of insurers' risk, since the insurer solvency represents all risks to which an insurer faces. It is supposed that the solvency ratio should have a meaningful relationship with insurance market- and macroeconomic-level factors as well as insurer's financial ratios which are representatives for different types of risks, where the solvency regime is a type of risk-based one. Comparing

[3]According to KPMG (2011), "*The Solvency II Directive is a new regulatory framework for the European insurance industry that adopts a more dynamic risk-based approach and implements a non-zero failure regime, i.e., there is a 0.5 percent probability of failure*".
[4] Solvency ratio is roughly defined here as a ratio of available capital to required capital (risk charge).

estimated values of model parameters in different solvency regimes can show how much a solvency regime based on risks is formulated.

Research questions and objectives

The research paper seeks answers for a set of significant questions: 1) "how the form of relationships between dependent and independent variables looks like?"; 2) "how the value of dependent variable changes, when independent variables are changing?" (that is, given independent values, how much a certain insurer is at insolvency risk?); 3) more specifically, "is the size really matter with regard to the solvency; how the financial stability of an insurer is related to its solvency; which types of risks (internal or external) are more influential on the solvency?"

Predicting solvent and insolvent insurers by ***Z***-score dependent variable is not our objective in this research paper. Instead, to develop a seminal model for explaining and predicting insurers' solvency ratio (a different dependent variable) is the main objective (in fact, insurer solvency ratio has not yet been modelled in the literature) of this paper. The subsidiary objectives are to:

1) Explore the form of relationships between dependent and independent variables,

2) Understand how the value of dependent variable changes when the independent variables are varied.

3) Determine whether solvency is mainly related to internal or external risks,

4) Define and introduce a novel model for evaluation of different solvency models by a statistical regression analysis based on risk-reflecting approach to solvency model evaluation, and then compare estimated regression models for different solvency regimes. It can show how much a solvency regime is grounded based on risks. It shows how much well a solvency model is formulated. The policy implications will help to correct any possible flaw in the solvency regime.

In particular, we are interested in studying how much solvency of an insurer respond to firm-level factors (those financial ratios indicating different types of insurer risks such as debt ratio, current ratio etc), market factors such as industry-combined ratio, and macro-economic factors such as interest rates. We are interested in finding out which type of factors (internal or external factors) has more relationship with dependent variable.

Several financial ratios such as debt ratio and current ratio are good variables indicating some types of risk (although they are not considered as measures of risk). We are interested in investigating how much the solvency ratio is meaningfully related to such risk-reflecting financial ratios. A comparison between different solvency systems reveals more information indicating different relationships of the solvency regimes or systems with risks. This is an ambitious objective of this article, since it intends to introduce a framework for the assessment of different solvency models (such as the Solvency I, the SST model, American RBC, Bests' Solvency model etc.) and compare them.

It should be clear that our approach is the risk-reflecting approach to solvency model evaluation based on the consensus that a good solvency model is a risk-sensitive model[5]. Our statistical regression model helps to see which solvency model is well risk-reflecting, i.e., its respective solvency ratio has a strong and meaningful relationship to the independent variables which are risk-reflecting in turn. Our approach to assessment is obviously differs from one that used by Grace, Harrington and Klein (1998)[6]. The study of relationship between the dependent variable and firm-level, industry-level variables as well as macro-economic conditions provides useful information for relevant stakeholders. By using this approach, stakeholders are able to figure out how much factors of different levels (firm, market and macro factors) affect the solvency of insurers in comparison. Using the model, stakeholders can understand that how variations in the firm-specific elements as well as the market and economic environments over time and across different companies may influence the solvency ratio. Further, stakeholders are able to predict how much in the form of solvency ratio an insurer at risk is. Applying the new model, we expect to overcome the problems of interest in the ***Z***-score models and to find answers for the above stated questions and realise the objectives. Therefore, the main objective of the paper is to develop a meaningful risk-reflecting model for solvency ratio of insurers.

Since 2012, solvency ratios (***Solvency***) of Iranian insurers are being disclosed on the website of the Central Insurance of IR Iran. For 2003 to 2011, solvency ratios calculated based on actual data of the insurers are available in Safari (2012). The data for variables of financial stability (***Z***) defined earlier, the size of insurer (***Assets***), capital to assets ratio (***CtoAssets***), return on assets (***ROA***) and loss ratio (***LoR***) are calculated based on book values. History (***Hist***) is the number of years an insurer is operating. Interest rate (***InterestR***) is an official interest rate for 1-year deposits. The variable listed (***Listed***) represents a value of 1 for those insurers listed in the Tehran Stock Exchange and 0 for otherwise in a certain year.

The predictive variables are considered among those financial ratios to be a representative for a type of insurers' risk, since the insurer solvency represents all risks an insurer faces to. It is supposed that the solvency ratio should have a meaningful relationship with market- and macro-level factors as well as insurer's financial ratios which are representatives for different types of risks. It is expected that the solvency ratio of insurance institutions has a meaningful relationship with financial stability (+), size of firm (no), history (no), capital to assets (+), loss ratio (-), return

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[5] As Olav Jones, Chairman CEA Solvency II Steering Group, expresses: "*One of the key objectives of Solvency II is to establish a solvency system that is better matched to the true risks of an insurance company*." (CEA and MERCER OLIVER WYMAN Limited, 2005).

[6] Grace, Harrington and Klein (1998) examine the classification power (the probability of correctly identifying a weak insurer as being weak) for two potential solvency detection methods. The first is to classify insurers using ratios based on risk-based capital (RBC) standards and the second is to use the Financial Analysis Tracking System (FAST) solvency screening mechanism created by the National Association of Insurance Commissioners (NAIC). They test the hypothesis that the RBC system has at least as much power for identifying financially weak insurers as the FAST scoring system does. Their empirical results are largely inconsistent with this hypothesis: RBC ratios are less powerful than FAST scores in identifying financially weak property-liability insurers during the sample periods. This evidence shows that the American Risk-Based solvency model is not sufficiently risk-reflecting. However, their approach to assessment of the solvency models is binary classification power of solvent and insolvent American insurers of period 1989-91 whose data contained in NAIC's RBC database.

on assets (+), listed in TSE (+) and interest rates (-). It is also expected that the market and macro-economic conditions (external factors) are less influential than firm-level factors.

Methodology and data

The primary purpose in the traditional literature around bankruptcy prediction is to examine the financial characteristics (independent variables) that distinguishes bankrupt from non-bankrupt companies. Bankruptcy prediction of companies is mainly done by Multiple Discriminant Analysis (MDA), Logistic Regression (LR), Probit regression, and Multinomial Regression (MLR).

In this paper, a multiple regression model is examined to find the best estimated solvency ratio model. In this article, the dependent variable is the solvency ratio of insurance companies. Though there is a similar ratio in banking system referred to as Capital Adequacy Ratio (CAR), also known as Capital to Risk (Weighted) Assets Ratio (CRAR), the solvency ratio is a specific ratio in insurance industry.

The proposed basic model is as $\boldsymbol{S = f\,(X_i, Y_j, Z_k)}$, where $\boldsymbol{S}$ is solvency ratio values of insurers, $\boldsymbol{X_i}$, $\boldsymbol{Y_j}$, and $\boldsymbol{Z_k}$ are firm, market- and macro-level independent variables respectively. The form of $\boldsymbol{f}$ is determined based on data analysis. The best model is found using model selection techniques. Since implementation of solvency systems such as Solvency I and Iranian solvency system, sufficient annual time series have not yet been generated for running a time series model.

Due to the limitation in availability of solvency ratio time series data, we may be interested to use panel data analysis. Some of the benefits of using panel data sets are listed in Hsiao (2007). Obvious benefits are data availability and a much larger data set with more variability and less co-linearity among the variables than is typical of cross-section or time-series data. With additional and more informative data, one can get more reliable estimates and test more sophisticated behavioral models with less restrictive assumptions. Similar to a typical panel data linear regression model, our model looks like $\boldsymbol{S_{it} = \alpha_{it} + \beta_{it}^{T} A_{it} + u_{it}}$, where $\boldsymbol{S}$ is the solvency ratio, $\boldsymbol{A}$ is $\boldsymbol{X}$, $\boldsymbol{Y}$ and $\boldsymbol{Z}$ sets of independent variables, $\boldsymbol{u}$ is error term, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are coefficients, $\boldsymbol{i=1,\ldots,\ n}$ and $\boldsymbol{t=1,\ldots T}$ are indices for insurers and time. The term $\boldsymbol{u_{it}}$ is a random disturbance term of mean 0.

In panel analysis, assumptions about the error term determine whether we speak of random or fixed effects (stochastically or non-stochastically variation of the error term). Random effects model is preferred under the null hypothesis due to higher efficiency, while under the alternative fixed effects model is at least consistent and thus preferred. For model selection of random effects or fixed effects, Hausman Test is utilized (Hausman, 1978). Estimation method (OLS, GLS, etc) which depends on the form of the model (Pooled or Panel) is selected after analysing the data and some relevant tests (e.g. F Test).

For model evaluation and validation, different appropriate criteria and tests are utilized. The model validation process can involve analyzing whether the regression residuals are random etc. The common criteria of goodness-if-fit (such as $\boldsymbol{R}$ squared, adjusted $\boldsymbol{R}$ squared, analysis of residuals such as statistics for serial correlation of the residuals and tests for the problem of heteroskedasticity etc.) for model validation will be utilized. To be comparable, solvency regime based on which the solvency ratio is calculated must remain the same across all companies and over the time. Time horizon of running the model entails a period of the solvency system enforcement.

The proposed model can subsequently be applied to the other solvency regimes where related observations are available.

For our multiple regression model $\boldsymbol{S_{it} = \alpha_{it} + \beta_{it}^T A_{it} + u_{it}}$, to be estimated applying panel data, the dependent solvency ratio $\boldsymbol{S}$ of insurers is modelled by insurer financial stability following the relevant literature as stated above measured as $\boldsymbol{Z \equiv (k+\mu)/\sigma}$, the size of insurer (indicated by book value of total assets), history (or oldness of insurer indicated by years of activity), capital to assets ratio, Return on Assets (ROA), loss ratio of insurer, listed in TSE (Tehran Stock Exchange) and interest rates (for 1-year deposits) as independent variables $\boldsymbol{A}$.

Most of data are financial ones which are available in accounting statements of insurers. Parts of data correspond to available market- and macro-economic variables. Almost all Iranian insurance institutions whose data are available are analysed in this study. Our panel analysis includes all Iranian insurers over a period of 2003 to 2012. Insurance solvency ratio is released by the authority since enacting related regulation (Directive No. 69 approved by Insurance High Council [of Iran]). We don't access to the relevant data of American or European insurers. So, at this stage, a evaluation of different solvency regimes in order to determine how much different solvency regimes based on risks are formulated is not possible, although this seems straightforward when data are available.

Overview of the insurance industry in Iran

Now, we give a picture from the current situation of insurance industry in Iran. By insurance industry in Iran, we mean a *commercial insurance industry* excluding all Iranian pension funds, Social Security Organization and its governmental market, Health Insurance Organization, Atiyeh Sazan Hafez (an unauthorized company) and all direct contracts to hospitals and clinics for health services by large organizations.

The official data in insurance industry of Iran is issued by Central Insurance of IR Iran. Insurance Industry Statistical Yearbook 1391 (CII, 2013) containing the latest data of 1391 (2012) is the latest issue.

According to CII (2013), in terms of the market size, total premium produced amounts 131097 billion Rials in 2012. The growth rates of total premium produced are 27.4, 45.5 and 52.3 in 2010 to 2012 respectively. Penetration rates (total produced premium to GDP) are 1.4, 1.4 and 1.9 in 2010 to 2012 respectively. So, this sector of the country's production grows faster than average in 2012. The world average of penetration rates are 6.9, 6.6 and 6.5 during these years. Loss ratios (paid loss to premium produced) are 78.6, 76 and 83 percent in 2010 to 2012 respectively.

In 2012, one state-owned insurance company (Iran Insurance Co.), 18 non-governmental insurance companies (Asia, Dana, Alborz, Moallem, Parsian, Karafarin, Mellat, Day, Saman, Novin, Pasargad, Mihan, Kowsar, Ma, Sina, Razi, Tose'e and Arman) in the main land and 6 insurance companies (Hafez, Omid, Iran Moein, Kish P&I Club, Qeshm P&I Club and Asmari Insurance Co.s) in free zones operated. Moreover, two reinsurance companies (Amin and Iranian Reinsurance

Co.s) were acting in the market in 2012. Most of these newly-established companies can be regarded as a captive (a subsidiary) company established by a bank or one of the Boniyads. Central Insurance of IR Iran was established in 1971 by the Act of Iranian Parliament for the purpose of regulating and supervising the insurance industry in Iran. Beside its regulatory and supervisory missions, it, by way of its Establishment Act, has been entrusted to carry out local compulsory reinsurance and to effect inward and outward reinsurance business in both national and international markets.

Almost all the companies are authorized to operate in all lines of business. Following the establishment of non-governmental insurance institutes law passed by the parliament in 2001, non-governmental institutes (6 institutes) are first authorized in 2003 after the Revolution and a few afterwards. With regard to sale channels and service providers, there are 19554, 25304 and 30958 agents, 324, 384 and 415 brokers, 47, 129 and 175 loss adjusters acting in the market in 2010 to 2012 respectively. Insurance companies directly employed 15438, 16333 and 17640 personnel (excluding sale channels and service providers) in 2010 to 2012 respectively.

The total premium written (portfolio of the premium) consists of 45% Motor Third Party Liability line of business followed by health (20%) in 2012. So, the portfolio concentrates in the third party, an obligatory line of business. Traffic accidents on Iran's roads cause ten thousands of deaths and injuries every year, and cost the country's economy billions of dollars (mostly imposed on the insurance industry). In Iran, traffic-related fatalities are the leading cause of death. During 2010 to 2012, road accidents cause 23249, 20068 and 19089 deaths. For 1380s this number amounts to 241000.

In terms of the market segmentation of the Iran insurance market by life and non-life, life lines of business possess 7.8% of the whole portfolio in 2012. Almost 1.3% of the portfolio consists of protection for oil and energy; therefore the oil and energy sectors absorb their coverage mainly from the abroad. Of the whole premium of the market, 45.6% belongs to Iran Insurance Co. in 2012. This state-owned company is the major and leading player in the market and dominates the market and prices.

The insurance industry possesses total assets (merged of all companies) of 170911 billion Rials in 2012. Of this value, almost 23% is belongs to the shareholders and the rest is debts (including insurance provisions). Almost 54% of the total assets are held in the form of receivables. For a period of 3 years from 2004 to 2006, Dana Insurance Company holds negative equity; while according to the Article 141 Commercial Law of Iran, if the accumulated loss exceeds half of the equity, the board has to invite the assembly to discuss the agenda of bankruptcy. However, Dana Co. is now active. In this year, the industry generated 4978 billion Rials dividend.

In terms of premium written compared to other countries, Iran is ranked 42 among all countries in 2012. Asian Reinsurance Corporation (Asian Re) is a regional inter-governmental corporation established in 1979 through the initiative of UN/ESCAP to operate as a professional reinsurer. International sanctions on Iran affected the industry in particular in access to high quality reinsurance market.

As a part of privatization plan, two governmental insurance companies (Asia and Alborz) were offered in Tehran Stock Exchange in 2009. Central Insurance of IR Iran and particularly one of its pillars, Insurance High Council, is the regulatory and supervisory authority. The Council is comprised of President of Central Insurance of IR Iran as its Head, Vice Ministers of Economic Affairs and Finance, Labor and Social Affairs, Commerce and Agriculture; together with five authorities and senior experts from the Iranian Insurance Market.

Insurance High Council passed a plan for de-tariffication in the insurance industry in 2009. By implementing this plan in all lines of business (excluding the third party) during two following years, the previous controls on price floors were relaxed and the market prices were liberalized. Further, as a part of this plan, it was approved that a financial regulation system would be replaced. Following the implementation of the market de-tariffication, a high competition in prices for grabbing market share formed; a situation that looked something like dumping. Insurance solvency system as the replacing financial regulation system was then approved by the Council in 2011 and enacted from the following year. Some complementary and relevant regulations to the solvency regulation were also approved in the following years.

Theoretical background

The traditional rationale for economic regulation is to protect the public interest by efficiently mitigating market failures. The test for whether government intervention into market activity will likely be efficient is two pronged (Breyer, 1982). First, there should be a demonstrable market failure compared to the standard of a reasonably competitive market characterized by (1) large numbers of sellers with relatively low market shares and low-cost entry by new firms, (2) low-cost information to firms concerning the cost of production and to consumers concerning prices and quality, and (3) an absence of material spillovers (i.e., all costs are internalized to sellers or buyers). Second, there should be substantial evidence that regulation can efficiently address any market failure; that is, that regulation's benefits will exceed its direct and indirect costs. Regulatory tools are necessarily imperfect (Harrington, 2005). Regulation always involves direct and indirect costs, and it risks unintended consequences. If both tests are met, efficient intervention then requires matching appropriate regulatory tools to specific market failures. Market structure and ease of entry are highly conducive to competition in most insurance markets. Modern insurance markets that are relatively free from regulatory constraints on prices and risk classification exhibit pervasive evidence of competitive conduct and performance. The principal imperfections that plausibly justify some degree of government regulation take the form of costly and imperfect information and spillovers. The primary rationale for insurance regulation is to improve efficiency by promoting safety and soundness and healthy competition in view of those problems.

Some form of solvency regulation is efficient because of costly/imperfect information and potential spillovers. For example, nonlife insurers bear enormous risk of loss from natural catastrophes and unexpected events. Liability insurers have paid hundreds of billions of dollars for claims brought many years after policies were sold, when legal liability standards and legal interpretations of policy provisions had changed substantially. The risk of many nonlife losses is very difficult to evaluate and price accurately. Insurers must hold large amounts of capital to maintain reasonably low probabilities of insolvency. Competition creates relentless pressure for low premiums, which in some cases may contribute to inadequate rates and increase insolvency risk, especially for difficult-to-price coverages subject to large but slow developing losses. With solvency regulation, policyholders that would find assessing and monitoring insurer insolvency risk very difficult (or who might have little incentive to do so on their own or using brokers or advisers) in effect delegate significant responsibility for monitoring to regulators. This rationale for solvency regulation is considerably stronger for direct (retail) insurance for personal lines than for larger commercial policyholders and reinsurance (wholesale) transactions. Regulatory monitoring might detect insurer financial problems early enough to prevent insolvency. In other cases, monitoring can help regulators intervene before the deficit between an insolvent insurer's assets and liabilities gets any larger. Some degree of regulatory restrictions on insurer risk taking (e.g., investment limitations and capital requirements) also is plausibly efficient (Harrington, 2005).

Limited, government-mandated protection of policyholders' claims against insolvent insurers is likely to be efficient, at least arguably, in view of costly or imperfect information and possible spillovers on other parties (such as those with legally valid workers' compensation or liability claims against policyholders of insolvent insurers). The insurance industry also has a collective interest in bonding its promises to pay claims. Given costly and imperfect information, in the absence of any guarantees insolvencies might damage the reputations of many insurers, including perhaps some financially strong ones, therefore motivating many or most insurers to participate in a joint guaranty system. Joint guarantees help maintain collective pressure for efficient solvency regulation by giving member insurers a direct stake in the outcomes of such regulation. Government-mandated systems reduce freerider problems and obviate antitrust concerns that might otherwise arise with privately initiated and managed joint guarantees.

The insurance business is characterized by a reversal of the conventional operating cycle. Insurance companies take in premiums, i.e., remuneration for insurance services rendered, before paying out any benefits in respect of claims. When they invest the funds thus collected, insurers run certain risks in respect of depreciation, liquidity, interest rates, matching assets and liabilities, credit, etc. In addition to these risks, which are common to all financial institutions, there are risks unique to the insurance industry- insufficient premiums, miscalculation of technical provisions, adverse change in loss frequency, catastrophic losses, reinsurance risk, etc. Lastly, like any business, an insurance company is subject to risks of a more general nature, such as incompetent or dishonest management or poorly managed growth.

The primary function of an insurer is to manage all these risks in such a way as to be able at all time (or at least in the vast majority of circumstances) to meet its commitments to policyholders and beneficiaries. It is this capability of an insurer to meet its commitments that is known as solvency. Nonetheless, because of the structure, size and complexity of the insurance industry, it is fairly difficult for policyholders or beneficiaries themselves to check their insurer's solvency. it is therefore for the primary purpose of protecting consumers that countries have instituted systems for supervising the solvency of insurance companies. Such supervision also makes it possible to guarantee the insurance industry's financial soundness and thus to enhance public confidence, which is vital to the industry's development (OECD, 2002).

How solvent is the company? In practice, this depends on the jurisdiction the company is in, and how the regulator defines the theoretical solvency levels. If the company has assets larger than some of these theoretical levels, then the company is in a “regulatory solvency state,” satisfying the statutory financial requirements (Sandström, 2011). So, there are different solvency systems in various jurisdictions evolving and promoting over time. Recent and modern solvency systems are risk sensitive.

In the EU, the concept of solvency margin has changed with the development of the EU directives. From the beginning it was seen as a supplementary reserve (Solvency 0). In the Solvency I non-life directive it is defined “to act as a buffer” (Sandström, 2006). The current solvency regime I in the EU is not adjusted to the true risks an insurance company runs. For this reason, the regulatory system is changed from Solvency I to Solvency II adopting Basel systems (I, II and III) in banking. Each developed countries in the Europe and all around the world has established a type of Risk-Based Capital (RBC) solvency system of its own which is sensitive to risk.

Overview of the solvency system in Iran

A solvency system which looks like an RBC (Risk-Based Capital) system was adopted and approved by the Council in 2011. Directive No. 69 (the solvency regulation) is in line with and a manifestation of Article 114, the 5th Development Plan. The Directive defines solvency as a capability of an insurer in terms of available capital to cover all insurers' risk. This regime does clearly give incentives to manage the risks better. The risks of an insurer are categorized in four classes including insurance risks, market risks, credit risks and liquidity risk. The insurance risk comprises of risks in 13 lines of business in addition to catastrophic risks (particularly earthquake risk). The market risk is estimated for stock portfolio as well as real estate assets. The credit risk considers receivables of an insurer. All debtors might not be able to or willing to settle their debts. Therefore this risk is the default risk of debtors to an insurer. The final category of risk which is considered in the solvency calculation of an Iranian insurer is the liquidity risk. This is the risk of the lack of sufficient liquidity or cash at any time.

For risk calculation, some risk factors are provided in the Directive. These factors of risks have been estimated applying the usual VaR (Value at Risk) models using available data of the insurance industry. Of this point of view, the solvency system is a static factor-based system like that currently used in the U.S. The system does not take into account a portfolio of risks meaning that the correlations between pairs of risks is assumed zero. Therefore, risks aggregation is simply an algebraic sum of risks. The solvency level of an insurer is determined based on the calculation of its solvency ratio (available capital to aggregated risks). According to the Directive, insurers possessing the solvency ratio of 100% and higher are regarded as the solvent insurers (level 1). Insurers having the solvency ratio lower than 10% are regarded as insolvent insurers and in this case Central Insurance of IR Iran will intervene to the end of bankruptcy. Insurers having the ratio in between have to provide some financial and recovery plans in order to strengthen their solvency levels at due time. These plans concentrate mainly on measures of reducing risks and increasing capital for strengthening solvency status.

Without involving in further details of the solvency system in Iran and of its counterparts in the other countries, this article needs only its outcome namely solvency ratio as the dependent variable.

Model estimation

For empirical model estimation, the plm add-on package available from the Comprehensive R Archive Network is used (See Croissant and Millo, 2008). A number of assumptions are usually made about the parameters, the errors and the exogeneity of the regressors, giving rise to a taxonomy of feasible models for panel data. The most common one is parameter homogeneity, which means that $\alpha_{it}= \alpha$ and $\beta_{it}=\beta$ for all i and t. The resulting model $S_{it} = \alpha + \beta^T A_{it} + u_{it}$ is a standard linear model pooling all the data across i and t. To model individual heterogeneity, one often assumes that the error term has two separate components, one of which is specific to the individual and does not change over time. This is called the unobserved effects model as $S_{it} = \alpha + \beta^T A_{it} + \mu_i + \varepsilon_{it}$. The appropriate estimation method for this model depends on the properties of the two error components. The idiosyncratic error ε_{it} is usually assumed well-behaved and independent from both the regressors A_{it} and the individual error component μ_i. The individual component may be in turn either independent from the regressors or correlated. If it is correlated, the ordinary least squares (OLS) estimator for β would be inconsistent. So it is customary to treat the μ_i as a further set of n parameters to be estimated, as if in the general model $\alpha_{it}=\alpha_i$ for all t. This is called the **fixed effects** (also known as **within** or **least squares dummy variables**) model, usually estimated by OLS on transformed data, and gives consistent estimates for β.

If the individual-specific component μ_i is uncorrelated with the regressors, a situation which is usually termed **random effects**, the overall error u_{it} also is, so the OLS estimator is consistent. Nevertheless, the common error component over individuals induces correlation across the composite error terms, making OLS estimation inefficient, so one has to resort to some form of feasible generalized least squares (GLS) estimators. This is based on the estimation of the variance of the two error components, for which there are a number of different procedures available.

If the individual component is missing altogether, pooled OLS is the most efficient estimator for β. This set of assumptions is usually labelled **pooling model**, although this actually refers to the errors' properties and the appropriate estimation method rather than the model itself. If one relaxes the usual hypotheses of well-behaved, white noise errors and allows for the idiosyncratic error ε_{it} to be arbitrarily heteroskedastic and serially correlated over time, a more general kind of feasible GLS is needed, called the **unrestricted** or **general GLS**. This specification can also be augmented with individual-specific error components possibly correlated with the regressors, in which case it is termed **fixed effects GLS**.

The **between model**, which is computed on time (group) averages of the data, discards all the information due to intra-group variability but is consistent in some settings (e.g., nonstationarity) where the others are not, and is often preferred to estimate long-run relationships. Variable coefficients models relax the assumption that $\beta_{it} = \beta$ for all i and t. Fixed coefficients models allow the coefficients to vary along one dimension, like $\beta_{it} = \beta_i$ for all t. Random coefficients models instead assume that coefficients vary randomly around a common average, as $\beta_{it} = \beta + \eta_i$ for all t, where η_i is a group- (time-) specific effect with mean zero. For more discussion of the issues and concepts see Baltagi (2005) and Wooldridge (2002).

For data analysis, our sample of 13 Iranian insurers entails Iran, Asia, Dana, Alborz, Moallem, Parsian, Karafarin, Omid, Mellat, Sina, Razi, Tose'e and Hafez Insurance Companies. These are Iranian insurers we have their annually time series data for a reasonable long time (2003-2012). Other Iranian insurers are those newly-established insurers lacking a reasonable data of time series, time-wise insufficient for our panel data analysis.

Since 2012, solvency ratios (***Solvency***) of Iranian insurers are being disclosed on the website of the Central Insurance of IR Iran. For 2003 to 2011, solvency ratios calculated based on actual data of the insurers are available in Safari (2012). The data for variables of financial stability (***Z***) defined earlier, the size of insurer (***Assets***), capital to assets ratio (***CtoAssets***), return on assets (***ROA***) and loss ratio (***LoR***) are calculated based on book values. History (***Hist***) is the number of years an insurer is operating. Interest rate (***InterestR***) is an official interest rate for 1-year deposits. The variable listed in TSE (***Listed***) represents a value of 1 for those insurers listed in the Tehran Stock Exchange and 0 for otherwise in a certain year. The variables ***Solvency***, ***Z***, ***Assets***, ***CtoAssets***, ***ROA***, ***LoR*** and ***InterestR*** are transformed into the Ln values.

Financial statements of the Iranian insurers are also published and available in their website as well as in the website of Tehran Stock Exchange (CODAL System) for listed companies. Extraction of or calculation of data for independent variables from or based on the financial statements are straightforward. Our independent variables including the financial stability, size, capital to assets ratio, return on assets ratio can be directly extracted or be simply calculated exploiting the financial statements. The data of history, loss ratio and listed variables are available in a series of Insurance Industry Statistical Yearbook issued by the Central Insurance of IR Iran. Official interest rates can be found in the website of the Central Bank of IR Iran.

Tests: As described in Croissant and Millo (2008), specification testing in panel models involves essentially testing for poolability, for individual or time unobserved effects and for correlation between these latter and the regressors (Hausman-type tests). As for the other usual diagnostic checks, the results of a suite tests are provided as following. The results of model estimation are also presented.

Tests of poolability also known as a *test for heterogeneity*: The hypothesis that the same coefficients apply to each individual is tested, i.e. if pooling is appropriate, the coefficients for individual units do not significantly differ from one another. It is a standard F test of stability (or Chow test) for the coefficients of a panel model, based on the comparison of a model obtained for the full sample and a model based on the estimation of an equation for each individual. The Table 1 indicates the results of the test.

Table 1: Result of Poolability Test by the Chow Test

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```
      F statistic

data:  Solvency ~ Assets + CtoAssets + ROA + Z + Hist + InterestR +  ...
F = 0.9344, df1 = 96, df2 = 13, p-value = 0.6061
alternative hypothesis: unstability
```

....

Based on the test results (F=0.9344 and p-value=0.6061), the null hypothesis of pooling model cannot be rejected and hence given the parameter homogeneity, that is $\boldsymbol{\alpha_{it}= \alpha}$ and $\boldsymbol{\beta_{it}=\beta}$ for all $\boldsymbol{i}$ and $\boldsymbol{t}$, the resulting model $\boldsymbol{S_{it} = \alpha + \beta^T A_{it} + u_{it}}$ is a standard linear pooling model. If $\boldsymbol{u_{it}}$ is i.i.d. across $\boldsymbol{i}$ and $\boldsymbol{t}$ and independent to $\boldsymbol{A_{it}}$, the OLS estimators for $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are consistent and unbiased.

Table 2 indicates the results of a pooling model estimated by the OLS using our sample data. According to the Table, the whole estimated model is significantly meaningful. Assets representing the size of the insurance institutes are negatively related to the solvency. This variable has a meaningful relationship. Whether or not an insurance institute is listed and further supervised by another authority is the other relevant factor that meaningfully has a positive relationship with the solvency. Financial stability, interest rate, history and ROA variables have also meaningful relationships at some levels of confidence, positively or negatively.

Table 2: Results of the pooling data model estimated by the OLS

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```
Oneway (individual) effect Pooling Model

Call:
plm(formula = Solvency ~Assets+CtoAssets+ROA+Z+Hist+InterestR+LoR+Listed, data=Data,model="pooling")

Balanced Panel: n=13, T=10, N=130

Residuals :
  Min. 1st Qu.  Median 3rd Qu.    Max.
-2.7800 -0.6500 -0.0151  0.7310  2.1900

Coefficients :
            Estimate Std. Error t-value  Pr(>|t|)
(Intercept) 15.115911   1.825043  8.2825 1.878e-13 ***
Assets      -0.363615   0.095541 -3.8058 0.0002232 ***
CtoAssets    0.024777   0.134626  0.1840 0.8542856
ROA          0.250199   0.137105  1.8249 0.0704877 .
Z            0.178104   0.071859  2.4785 0.0145709 *
Hist        -0.418072   0.136172 -3.0702 0.0026418 **
InterestR    2.813243   0.596174  4.7188 6.428e-06 ***
LoR         -0.055884   0.143367 -0.3898 0.6973696
Listed       0.727761   0.317304  2.2936 0.0235403 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Total Sum of Squares: 340.89
Residual Sum of Squares: 124.36
R-Squared : 0.63519
Adj. R-Squared : 0.59122
F-statistic: 26.3355 on 8 and 121 DF, p-value: < 2.22e-16

....

*Tests for serial correlation***:** The models with individual effects have composite errors that are serially correlated by definition. The presence of the time-invariant error component gives rise to serial correlation which does not die out over time. Thus standard tests applied on pooled data always end up rejecting the null of spherical residuals. There may also be serial correlation of the usual kind in the idiosyncratic error terms, e.g., as an AR(1) process. The latter kind of dependence for serial correlation is considered here. For these reasons, the subjects of testing for individual error components and for serially correlated idiosyncratic errors are closely related (Croissant and Millo, 2008). In particular, marginal tests for one direction of departure from the hypothesis of spherical errors usually have power against the other one: in case it is present, they are substantially biased towards rejection. Joint tests are correctly sized and have power against both directions, but usually do not give any information about which one actually caused rejection. Conditional tests for serial correlation that take into account the error components are correctly sized under presence of both departures from sphericity and have power only against the alternative of interest. While most powerful, if correctly specified, the latter, based on the likelihood framework are crucially dependent on normality and homoskedasticity of the errors (Croissant and Millo, 2008). Now, joint, marginal and conditional ML-based tests, plus some semi-parametric alternatives which are robust versus heteroskedasticity and free from distributional assumptions are provided. The *unobserved effects test of Wooldridge* (Wooldridge, 2002), is a semi-parametric test for the null hypothesis that $\sigma^2_\mu = 0$, i.e., there are no unobserved effects in the model. If the standard random effects assumptions hold but the model does not actually contain an unobserved effect, pooled OLS is efficient and all associated pooled OLS statistics are asymptotically valid. The absence of an unobserved effect is statistically equivalent to $\mathbf{H_0}$**:** $\sigma^2_\mu = 0$. The test is valid under error heteroskedasticity and departures from normality (Wooldridge, 2002). According to Table 3, the null hypothesis of existence of unobserved individual effects in the pooling model estimated by the OLS method cannot be rejected. Therefore, the results of the pooling model estimated by the OLS seem not to be valid. The test can detect many kinds of serial correlation in the composite error, and so a rejection of the null should not be interpreted as implying that the random effects error structure must be true (Wooldridge, 2002).

Table 3: Wooldridge's test for unobserved individual effects

....

Wooldridge's test for unobserved individual effects

data: formula
z = 1.7792, p-value = 0.0752
alternative hypothesis: unobserved effect

....

*Tests for individual and time effects***:** The Breusch–Pagan LM statistic, tests the null hypothesis that the pooled OLS estimator is adequate against the random effects alternative. The tests implement Breusch and Pagan (1980) Lagrange Multiplier tests of two-ways, individual, and time effects based on the results of the pooling model. The null hypothesis state that the random effects model is not appropriate and the OLS would be consistent (Brooks, 2008). The results of the tests in Table 4 indicate that two-ways and individual effects are meaningfully better models for our data sample. In fact, there exists a meaningful individual effect in the sample data. Individual dimension of our sample data is longer than its time dimension.

Table 4: Result of Lagrange Multiplier Test by the Breusch and Pagan Test

....

```
    Lagrange Multiplier Test - two-ways effects (Breusch-Pagan)

data:  Solvency ~ Assets + CtoAssets + ROA + Z + Hist + InterestR +  ...
chisq = 17.6775, df = 2, p-value = 0.000145
alternative hypothesis: significant effects
```

....

```
    Lagrange Multiplier Test –individual effects (Breusch-Pagan)

data:  Solvency ~ Assets + CtoAssets + ROA + Z + Hist + InterestR +  ...
chisq = 17.4444, df = 1, p-value = 2.958e-05
alternative hypothesis: significant effects
```

....

```
    Lagrange Multiplier Test - time effects (Breusch-Pagan)

data:  Solvency ~ Assets + CtoAssets + ROA + Z + Hist + InterestR +  ...
chisq = 0.2331, df = 1, p-value = 0.6292
alternative hypothesis: significant effects
```

....

The pooled OLS estimator, indeed, ignores the panel structure of the data and simply estimates $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ where the whole observations across $\boldsymbol{i}$ and $\boldsymbol{t}$ are treated as a cross-section dimension. Usual OLS standard errors are not reliable because it does not consider heterogeneity across groups or time. The pooled OLS estimator of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ is unbiased under several classical assumptions in small samples. Moreover, the pooled OLS estimator is not efficient. More importantly, the usual standard errors of the pooled OLS estimator is incorrect and tests (t, F, z, Wald tests) based on them are not valid. If $\boldsymbol{\mu_i}$ is omitted and potentially correlated with the other regressors, then the pooled OLS estimator is of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ is biased and inconsistent.

Table 5 indicates the results of the same previous model except for including dummy variables for the time dimension (time-demeaning model). The new model is also termed Least Squares Dummy Variables (LSDV), or within or Fixed Effect (FE) model (Croissant and Millo, 2008). The estimated model is meaningful with regard to the presence of individual effects in the sample data.

Table 5: Results of the LSDV model

....

```
Oneway (individual) effect Within Model

Call:
```

```
plm(formula = Solvency ~ Assets + CtoAssets + ROA + Z + Hist +
    InterestR + LoR + Listed, data = Data, model = "within")

Balanced Panel: n=13, T=10, N=130

Residuals :
   Min. 1st Qu.  Median 3rd Qu.    Max.
-2.0300 -0.5320  0.0124  0.4590  1.7200

Coefficients :
          Estimate Std. Error t-value  Pr(>|t|)
Assets     0.350124   0.163565  2.1406  0.034537 *
CtoAssets  0.176508   0.306600  0.5757  0.566009
ROA       -0.075668   0.203040 -0.3727  0.710114
Z          0.557593   0.279162  1.9974  0.048275 *
Hist      -1.021718   0.248205 -4.1164 7.505e-05 ***
InterestR  1.930912   0.620679  3.1110  0.002381 **
LoR       -0.072360   0.135278 -0.5349  0.593813
Listed     0.530894   0.306191  1.7339  0.085769 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    131.22
Residual Sum of Squares: 75.641
R-Squared      :  0.42357
      Adj. R-Squared :  0.35515
F-statistic: 10.0118 on 8 and 109 DF, p-value: 2.2473e-10
.................................................................................................................................
Estimated Fixed effects:
       1        2        3        4        5        6        7        8
2.843475 1.988054 5.592656 5.203631 3.100540 2.874264 3.143650 4.799413
       9       10       11       12       13
2.973933 4.696114 3.978680 3.779647 4.515107
.................................................................................................................................
```

Test for Fixed or Random Effects model: Hausman test is based on the comparison of two sets of estimates (Hausman, 1978). The Hausman test is a kind of Wald ChiSquare test with k-1 degrees of freedom (where k = number of regressors) on the difference matrix between the variance-covariance of the LSDV with that of the Random Effects model. If the null hypothesis that the individual effects are uncorrelated with the other regressors in the model is not rejected, a random effect model is better than its fixed counterpart.

Table 6 presents the results of the Hausman test for determining appropriateness of Fixed or Random effect model. As the table shows, the Chi-square value of the test is 19.35 and the p-value is 0.013. The null hypothesis can therefore not be rejected and at the 95% significance level the Random Effect model is preferred.

Table 6: Results of the Hausman test for Fixed or Random Effects model

```
.................................................................................................................................
       Hausman Test

data:  Solvency ~ Assets + CtoAssets + ROA + Z + Hist + InterestR +  ...
```

```
chisq = 19.3465, df = 8, p-value = 0.01311
alternative hypothesis: one model is inconsistent
```

If the one-way (individual) Effects Random Effects model is the true model for Iranian insurer's solvency, then the relationships between independent and dependent variables are those shown in the Table 7. The Individual Effect Random Effect model fits the data well at the .01 significance level (F= 12.9, p= 2.5275e-13). R^2 of 0.46 says that this model accounts for 46 percent of the total variance. The model has the intercept of 9.69 and the slopes contained in the Table.

Table 7: Results of Random Effects model

```
Oneway (individual) effect Random Effect Model
  (Swamy-Arora's transformation)

Call:
plm(formula = Solvency ~ Assets + CtoAssets + ROA + Z + Hist +
    InterestR + LoR + Listed, data = Data, model = "random")

Balanced Panel: n=13, T=10, N=130

Effects:
              var std.dev share
idiosyncratic 0.6940  0.8330  0.67
individual    0.3417  0.5845  0.33
theta:  0.5891

Residuals :
   Min. 1st Qu.  Median 3rd Qu.    Max.
-2.3900 -0.5870  0.0279  0.4460  1.9300

Coefficients :
            Estimate Std. Error t-value  Pr(>|t|)
(Intercept)  9.692871   2.313701  4.1893 5.344e-05 ***
Assets       0.017480   0.123147  0.1419 0.8873569
CtoAssets   -0.020147   0.201071 -0.1002 0.9203517
ROA         -0.050795   0.169864 -0.2990 0.7654298
Z            0.340744   0.120534  2.8270 0.0055003 **
Hist        -0.847615   0.183039 -4.6308 9.242e-06 ***
InterestR    2.279765   0.570549  3.9957 0.0001112 ***
LoR         -0.075033   0.130774 -0.5738 0.5671919
Listed       0.660661   0.298468  2.2135 0.0287375 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    166.62
Residual Sum of Squares: 89.865
R-Squared      :  0.46065
      Adj. R-Squared :  0.42876
F-statistic: 12.918 on 8 and 121 DF, p-value: 2.5275e-13
```

Locally robust tests for serial correlation or random effects: The presence of random effects may affect tests for residual serial correlation, and the opposite. One solution is to use a joint test, which has power against both alternatives. A joint LM test for random effects and serial correlation under normality and homoskedasticity of the idiosyncratic errors has been derived by Baltagi and Li (1991) and Baltagi and Li (1995). Table 8 presents the results of the joint LM test for random effects and serial correlation under normality and homoskedasticity of the idiosyncratic errors. Based on the results of test, there are no random effects or serial correlation (under normality and homoskedasticity) in the idiosyncratic errors of the estimated Random Effects model. Rejection of the joint test, though, gives no information on the direction of the departure from the null hypothesis, i.e., the rejection is due to the presence of serial correlation, of random effects or of both.

Table 8: Results of the Baltagi and Li AR-RE joint test

....

```
	Baltagi and Li AR-RE joint test

data:  formula
chisq = 54.3374, df = 2, p-value = 1.689e-13
alternative hypothesis: AR(1) errors or random effects
```

....

Locally robust tests for serial correlation or individual random effects: Bera, Sosa-Escudero, and Yoon (2001) derive locally robust tests both for individual random effects and for first-order serial correlation in residuals as corrected versions of the standard LM test. While still dependent on normality and homoskedasticity, these are robust to local departures from the hypotheses of, respectively, no serial correlation or no random effects. The authors observe that, although suboptimal, these tests may help detecting the right direction of the departure from the null, thus complementing the use of joint tests. The results of this test (Chisq: 36.893 and p-value: 1.248e-09) in Table 9 shows that the null hypothesis of no individual random effects or serial correlation in the residuals of the estimated Random Effect model cannot be rejected. This evidence additionally supports the results of random effects estimation.

Table 9: Results of the Bera, Sosa-Escudero and Yoon locally robust test

....

```
	Bera, Sosa-Escudero and Yoon locally robust test

data:  formula
chisq = 36.893, df = 1, p-value = 1.248e-09
alternative hypothesis: AR(1) errors sub random effects
```

....

Conditional LM test for AR(1) or MA(1) errors under random effects: Baltagi and Li (1991 and 1995) derive a Lagrange multiplier test for serial correlation in the idiosyncratic component of the errors under (normal, heteroskedastic) random effects. Under the null of serially uncorrelated errors, the test turns out to be identical for both the alternative of AR(1) and MA(1) processes. Table 10 reflects the results of the test showing no serial correlation in the idiosyncratic component of the errors under (normal, heteroskedastic) random effects. This evidence also additionally supports the results of random effects estimation.

Table 10: Results of the Baltagi and Li one-sided LM test

```
..........................................................................................
    Baltagi and Li one-sided LM test

data:  Solvency ~ Assets + CtoAssets + ROA + Z + Hist + InterestR +     LoR + Listed
z = 5.4676, p-value = 2.28e-08
alternative hypothesis: AR(1)/MA(1) errors in RE panel models
..........................................................................................
    Baltagi and Li two-sided LM test

data:  Solvency ~ Assets + CtoAssets + ROA + Z + Hist + InterestR +     LoR + Listed
chisq = 29.8951, df = 1, p-value = 4.561e-08
alternative hypothesis: AR(1)/MA(1) errors in RE panel models
..........................................................................................
```

Tests for cross-sectional dependence: Another important test is for cross-sectional dependence. This could arise, if in the data, individuals respond to common shocks (as in the literature on factor models) or if spatial diffusion processes are present, relating individuals based on distance. If cross-sectional dependence is present, the consequence is, at a minimum, inefficiency of the usual estimators and invalid inference when using the standard covariance matrix. This is the case, e.g., if in an unobserved effects model when cross-sectional dependence is due to an unobservable factor structure, with factors that are uncorrelated with the regressors. In this case the within or random estimators are still consistent, although inefficient (De Hoyos and Sarafidis 2006). Therefore, in order to perform valid inference, first cross-sectional dependence by using Pesaran's CD test (Pesaran 2004) is detected and then robust covariance matrices are provided. Pesaran's CD test, which is an *LM-type test for global cross-sectional dependence*, is appropriate both in ***N***- and in ***T***-asymptotic settings. It has remarkable properties in samples of any practically relevant size and is robust to a variety of settings. The only drawback is that the test loses power against the alternative of cross-sectional dependence if the latter is due to a factor structure with factor loadings averaging zero, that is, some units react positively to common shocks, others negatively (Croissant and Millo, 2008). It tests the null hypothesis of zero dependence across the panel members. Like the Pesaran CD test, the Breusch-Pagan and Scaled LM tests, which are *LM-types test for cross-sectional dependence* , are originally meant to use the residuals of separate estimation of one time-series regression for each cross-sectional unit in order to check for cross-sectional dependence. If a different model specification (within, random, ...) is assumed consistent, one can resort to its residuals for testing (which is common, e.g., when the time dimension's length is insufficient for estimating the heterogeneous model).

The results of the tests for cross-sectional dependence for Individual Random Effects model are appeared in Table 11. According to the Pesaran CD test, the null hypothesis of zero dependence across individuals cannot be rejected. However, with regard both to the Breusch-Pagan LM test and the Scaled Breusch-Pagan LM test for cross-sectional dependence, the null hypothesis is rejected.

Table 11: Results of the tests for cross-sectional dependence for Individual Random Effects model

```
........................................................................................................................................
        Pesaran CD test for cross-sectional dependence in panels

data:  formula
z = 1.3811, p-value = 0.1672
alternative hypothesis: cross-sectional dependence
........................................................................................................................................
       Breusch-Pagan LM test for cross-sectional dependence in panels

data:  formula
chisq = 148.4677, df = 78, p-value = 2.662e-06
alternative hypothesis: cross-sectional dependence
........................................................................................................................................
       Scaled LM test for cross-sectional dependence in panels

data:  formula
z = 5.6419, p-value = 8.408e-09
alternative hypothesis: cross-sectional dependence
........................................................................................................................................
```

Results and findings

While the results of test for heterogeneity indicate evidence in favour of poolability (Table 1) and the results of pooling data model estimated by the OLS show off a meaningful model (Table 2), the results of Wooldridge's test for unobserved individual effects (Table 3) as well as the results of the Breusch–Pagan LM test (Table 4) invalidate the results of the pooling model estimated by the OLS. In fact, there exists individual effect in our sample data.

According to the results of Hausman test (Table 6), the Random Effect model is preferred for the sample data. Therefore, the one-way (individual) Effects Random Effects model seems the true model for Iranian insurer's solvency. The Individual Effects Random Effects model fits the data well at the .01 significance level and it accounts for 46 percent of the total variance (Table 7).

The Baltagi and Li AR-RE joint test for random effects and serial correlation of the idiosyncratic errors (Table 8), the Bera, Sosa-Escudero and Yoon locally robust test for individual random effects and for first-order serial correlation in residuals (Table 9) and the Baltagi and Li one and two-sided LM tests for serial correlation in the idiosyncratic component of the errors under (normal, heteroskedastic) random effects (Table 10) assert the validity of the Individual Effects Random Effects model. However, the Pesaran's CD test for cross-sectional dependence in the model (Table 11) expresses the null hypothesis of zero dependence across individuals cannot be rejected. In contrast, with regard both to the Breusch-Pagan LM test and the Scaled Breusch-Pagan LM test for cross-sectional dependence (Table 11), the null hypothesis is rejected implying existence of zero dependence across individuals.

Based on tests, the Individual Effects Random Effects model looks like a valid and reliable model for solvency ratio of Iranian insurers. The results of the model indicate there is a meaningful positive intercept for the model. As Table 7 indicates, assets (***Assets***) as proxy for size of insurer have positive relationship with dependent variable. But it is not meaningful. The ratio of capital to assets (***CtoAssets***) is expected to have a positive and meaningful relationship with the dependent variable. Contrary to the expectation, this variable behaves adversely in the model, although its behaviour is far from significance. The return on assets (***ROA***) surprisingly behaves in the same way of the ***CtoAssets***. It has no impact on the solvency ratio. The variable of financial stability ***Z***, as expected, significantly makes a positive relationship with the solvency of insurer. History (***Hist***) is negatively related to the solvency with a high value. Interest rate (***InterestR***) as a macroeconomic factor positively contributes to strongly explain the solvency of insurers. The variable loss ratio (***LoR***) relates to the solvency of Iranian insurers negatively as expected. The variable listed in TSE (***Listed***), as reasonably expected, suggests a positive and relatively strong relationship meaning that the second regulator and supervisor would result to a higher solvency ratio.

A comparison of the estimated LSDV model (Table 5) and the estimated Individual Effects Random Effects model (Table 7) reveals some facts. In terms of goodness-of-fit, the Individual Effects Random Effects model with F=12.92 and p-value=2.5275e-13 and the LSDV model with F=10.01 and p-value=2.2473e-10 should be preferred. The Individual Effects Random Effects model accounts for 46 percent of the total variance compared to 42.4 percent R^2 of the LSDV. In terms of the relationships and without regard to the intercept in the Individual Effects Random Effects model, the results of the estimated models look almost the same (except for the variable Capital to assets).

Analysis and interpretation of the results

Perhaps the most fundamental difference between fixed and random effect is of inference. The fixed-effects analysis can only support inference about the group of measurements. The random-effects analysis, by contrast, allows inferring something about the population from which the sample is drew. If the effect size in each subject relative to the variance between the subjects is large enough, it can be guessed (given a large enough sample size) that the population exhibits that effect. If the fixed effects model is used on a random sample, it cannot be made inferences outside the data set. Random effects assume a normal distribution, so one can make inferences to a larger population. The fixed effect model assumes that no other factors are effecting changes in data over the period t_0 to t_1 not including this will result in omitted variable bias. In random effect model, instead of thinking of each unit as having its own systematic baseline, we think of each intercept as the result of a random deviation from some mean intercept. Because the sample data appeared to have individual-level (i.e., insurance company level) clustering, the one-way random effects model was used. Based on the sample data, time does not play a significant role in relationships between the solvency and the explanatory variables such as financial stability and other factors.

The results of the estimated model indicate there is a meaningful positive intercept for the model. Assets (***Assets***) as a proxy for size of insurer have positive relationship with dependent variable. But it is not meaningful. As it was expected, the size factor has no relationship with the solvency. In reality, the size does not play a role in solvency, i.e., the size factor is not regarded as an influential factor in calculation of the solvency ratio. Without any interpretation, solvency ratio doesn't have association to assets maybe because assets appear in balance sheet in book value. A large part of assets in book value doesn’t significantly change over time. Larger insurers are not necessarily more solvent or healthy. Even with regard to the concept of "Too big to fail", bigger insurers face to systemic risk. The risk opposes the solvency. Of the other side, agile small businesses seem not to be more solvent.

The ratio of capital to assets (***CtoAssets***), contrary to the expectation, behaves adversely in the model. The negative relationship between the solvency and the ***CtoAssets*** may imply that additional capital does not eventually lead to the higher solvency. Additional capital is somehow spent in the form of one of the insurer's assets. The new asset may increase further risks. The new asset financed by additional capital may appear in the form of e.g., investments in risky stocks leading to further risks for insurer. Further risks decrease the solvency. Therefore, additional capital may not necessarily help to strengthening solvency per se. It should be considered that where the capital is actually spent. The sign of this variable may be a signal of how the additional capital is actually spent in sample insurers. All in all, additional capital positively affects numerator (available capital) of the solvency ratio and negatively affects denominator of the solvency ratio (risks in the ratio). The final outcome can be positive or negative depending on how fast the available capital and risks are relatively growing. It has to be regarded whether additional capital results eventually to strengthening solvency or not, considering how it is spent.

The ratio of capital to assets is simply the equity over total assets. Debt ratio is the complement of the Capital to Assets (Debt Ratio=100%-Capital to Assets Ratio). In an insurance company, the debts include provisions. Provisions are reserves and resources for settlement of claims. As much as the ***CtoAssets*** increases, the Debt Ratio decreases meaning that the insurer does not afford sufficient resources for claim settlements. In fact, there exists a paradox between *Capital Adequacy* and *Provisions Adequacy* of an insurer. So, in the financial structure of an insurer, there should be one of either capital adequacy or provision adequacy. This paradox also is true for banks. If the variable ***CtoAssets*** makes a positive relationship with the in the model, then the Debt Ratio has to make a negative relationship with the solvency ratio meaning that the insurer would be as more solvent as much as its provisions diminishes. However, this is not right. As it was mentioned earlier, provisions are resources for claim settlement. One solution to the paradox gets back to the assets quality. For available capital and eventually solvency calculation, the regulators consider the quality of assets by categorization of assets in different tiers, although this is not the absolute solution for the paradox.
The Iranian regulator usually requires insurers involving lower levels of solvency bring capital in order to strengthen the solvency status. What happened in reality during recent years is that the insurers legally re-evaluate their fixed assets such as constructions. According to the Directive No. 69, the insurer may re-evaluate their fixed assets. The excess of re-evaluated assets is a permissible new capital. However, this is an accounting capital. Indeed, no new capital is injected into the company by this method. Asia Insurance Co. is an example of a company suffering from low level of solvency. The company's solvency was strengthened by this way.

The return on assets (***ROA***) surprisingly behaves in the same way of the ***CtoAssets***. It has no significant impact on the solvency ratio. Profitability should inherently have a positive influence on the solvency. Profitability increases cash inflow. Therefore, any increase in financial resources, particularly from inside should lead to an increase in the solvency.

The variable of financial stability of insurer ***Z***, as expected, significantly makes a positive relationship with the solvency of insurer implying that financially stable insurers are more solvent. This means that stable insurers are more solvent and less likely to go bankrupt. Although the variables ***CtoAssets*** and ***ROA*** have no relationship with the solvency, the combined variable of financial stability measured as $Z \equiv (k+\mu)/\sigma$, where k is equity capital as percent of assets (equal to ***CtoAssets***), μ is return as percent of assets (equal to ***ROA***) and σ is standard deviation of μ (risk of ***ROA***), has a significant relationship with the dependent variable. The model does not indicate any sign pointing out that the financial stability cause solvency or vice versa. This causality test needs further investigations.

History (***Hist***) is negatively related to the solvency with a high value. Given the solvency ratio is available capital to the amount of aggregated risks, the reason for negativity of the relation is that the newly-established companies bring a relatively large amount of capital without considerable risks in the first years of operation. The main risk of Iranian insurer like their counterparts in many countries is inherently underwriting risk (Safari, 2012). Underwriting risk is paramount for nonlife insurers (Harrington, 2005). In the first years of operation, the newly-established companies cannot take over a large amount of insurance risk. Without sufficient experience, they cannot rapidly access to a high market share in particular where the market is competitive. Moreover, new companies do not have a high market risk because they do not possess a large amount of financial resources for investment. Their paid capital is mainly spent for purchasing official buildings. Further, the new companies do not face to the credit risk of their debtors due to low scale of sales in the first years. So, newly-established companies have a low risk (mainly insurance risk). Thus, the solvency ratios of new companies are analogously higher than older companies. The older the company the higher the risk is and hence the lower solvency is. This is not absolutely true but with regard to our data sample, such a conclusion looks like a reality. Therefore, the history has reasonably a negative relationship with the solvency. It is worth mentioning that, the time period of our sample data comprises a period during which most of Iranian insurers established.

Regarding the solvency ratio (available capital to aggregated risk charges), negative sign of the History (***Hist***) in the model using our data sample of Iranian insurers implies that all in all the growth rate of risks is higher than growth rate of capitalization in Iranian insurers.

Interest rate (***InterestR***) as a macroeconomic factor positively contributes to strongly explain the solvency of insurers. A strong effect of interest rates on insurance markets is acknowledged by many economists. There is no consensus on the nature of the relationship between interest rates and the insurance industry performance. Equity, underwriting profitability and supply of insurance all appear to be affected by interest rates. Although interest rate changes are systematic and affect the entire insurance sector across all lines simultaneously, empirical results differ, as well as theoretical explanations for such results (Tarasov, 2013). Influence of interest rates on decisions for purchase and on many variables of insurers can be seen from the sides of demand as well as of supply.

It should be noted that the portfolio of premiums of Iranian insurers consists of 45% Motor Third Party Liability line of business which is obligatory both for motor vehicle holders and insurers. The portfolio also contains 7.8% all life lines of business. Therefore, interest rates have empirically no impact on premiums written and in turn on operational profitability and eventually solvency of insurers. Interest rates can positively affect profitability of the insurers on their investments. The main part of profits is usually earned from investments compared to underwriting operations. Investment profits compared to underwriting profits are considerable and sometimes exceeds. For example in 2012, 48% of gross income of insurance industry in Iran stemmed from investments. According to Directive No. 60 (Investments of insurers) approved by Insurance High Council of Iran, insurers are required to invest at least 30% of their eligible financial resources as deposits. This remarkable amount is directly affected by the interest rates.

The variable loss ratio (***LoR***) relates to the solvency of Iranian insurers negatively as expected. The relationship is not meaningful. Loss paid is considered as the largest cost in an insurance company. This is a main cash outflow.

The variable ***Listed***, as a market level factor, suggests a positive relationship which may imply that the second supervisor would result to a higher solvency ratio. This may mean that, the second supervisor really works and is efficient. This relationship does not show any causality. The stock exchange imposes its own regulations and conditions. Only eligible insurers obtaining eligibility requirements of the Tehran Stock Exchange (some financial health and strength requirements) are listed. So, the positive relationship may imply that only healthier and more solvent insurers are listed. Of the other side, the positive relationship may imply that the second supervisor can help insurers achieve the higher levels of the solvency. A causality test may reveal further results and findings.

Conclusion and policy implications

The article suggests a seminal idea of modelling insurance solvency ratio. A multiple regression model ($\boldsymbol{S_{it} = \alpha_{it} + \beta_{it}^T A_{it} + u_{it}}$) is proposed to be estimated applying panel data. While the results of test for heterogeneity indicate evidence in favour of poolability and the results of pooling data model estimated by the OLS show off a meaningful model, the results of some relevant tests invalidate the results of the pooling model. Based on the results of Hausman test, the Random Effect model is preferred for 13 sample data of Iranian insurers for a period of 2003 to 2012. The tests indicate that there exists individual effect in the sample data. Therefore, the one-way (Individual) Effects Random Effects model seems the true model for Iranian insurer's solvency. The Individual Effects Random Effects model fits the data well at the .01 significance level and it accounts for 46 percent of the total variance. Several relevant tests (such as the Baltagi and Li AR-RE joint test, the Bera, Sosa-Escudero and Yoon, the Breusch-Pagan LM test and the Scaled Breusch-Pagan LM test) stress on validity and reliability of the Individual Effects Random Effects model.

The results of model estimation reveal a meaningful positive relationship between the independent variables financial stability, interest rate and listing in TSE and the dependent variable solvency as well as a meaningful negative relationship between the independent variable history and the dependent variable solvency. Other independent variables including size, capital to assets ratio, return on assets ratio and loss ratio pose no relationship.

These findings simply assert that more stable and listed insurers have higher levels of solvency. Moreover, higher interest rates correspond to higher levels of solvency. In contrast, any change in total assets of insurers (the size variable), capital to assets ratio, return on assets ratio and loss ratio has nothing to do with the solvency levels of Iranian insurers.

Total assets have no relationship with the solvency. Therefore, a large insurer is not necessarily more solvent. As such, agile small insurers seem not to be more solvent. Become larger by means of grabbing more market share and issuing further policies at any cost in order to increase cash inflow seems not to be a good way through which current Iranian insurers are hurriedly running. Currently Iranian insurers try to access further market share by means of price dumping ignoring their solvency position. Their solvency position is harmed by offering products in low prices. Some of Iranian insurers such as Day and Tose'e Insurance Companies have been recently intervened by the regulator so that they might go to bankrupt. Day for example is banned to issue further Third Party policy. They are now in financial difficulties because of issuing unreasonable policies with very low prices.

There is currently an external pressure from some politicians to reduce the price of the third party policy neglecting its impact on cash inflow and in turn on the solvency. This may influence the financial position of Iranian insurers due to the high portion of this line of business in the portfolio of premiums. Blood money price is determined outside the industry. This rate is also a relevant and very influential due to due to the high portion of third party.

Based on the results, additional cash and capital at any cost and without regard to the fact that how these are spent may lead to undesired outcomes. If attaining higher levels of solvency is the target both for insurers and the regulator, they should seriously pay their attention to final point where additional capital and cash inflows are spent. The Directive 69 disregards and is silent about where exactly additional capital should be spent. Additional capital should be planned to be led into more safe types of assets avoiding risky assets. The Directive should be revisited. Accounting capital stemmed from changes in accounting procedures, specifically from re-evaluation of fixed assets is a short-term solution for companies suffering from lower levels of solvency. these companies should be required to bring real capital.

Financial stability of insurers should be highly considered, since stable insurers are more solvent and less likely to go bankrupt. Financial stability may mean less risk and less risk may lead to higher solvency. The risks including the risk of fluctuations in returns have to be more closely controlled. Unstable insurers should be earlier detected and more closely onsite inspected. Causes should be explored. This needs a transparent procedure. The regulator (Central Insurance of IR Iran) lacks a transparent procedure for onsite inspection of insurers involving financial instability and difficulties.

Based on our results, the older the company the higher the risk is and hence the lower solvency is. This is not a universal theory. Insurance industry in Iran is emerging and the market has many signs of an emerging market. This conclusion should be taken into account with regard to the fact that, the time period of our sample data comprises a period during which most of Iranian insurers established. In such an atmosphere the growth rate of risks in an insurer may exceeds its growth rate of capitalization. The rate of change in risk in comparison to the rate of change in capital should be monitored and controlled both by insurers and the regulator. Some policies or rules may be needed to restrict insurers hurriedly issue third party and health policies. The third party and health lines of business involve a high loss ratio. These lines of business bring more risk than cash into the company.

Listed insurers afford higher levels of solvency. This may mean that the second supervisor would result to a higher solvency ratio implying the second supervisor really works and is efficient. If this is true, the insurers should be encouraged for offering their equity in the TSE. To become listed has the advantage of strengthening the solvency in addition to accessing to further capital.

The basic idea of the article is applicable to the other financial institutes. Thus, it is possible to develop a similar model for, e.g., Capital Adequacy Ratio (CAR), also known as Capital to Risk (Weighted) Assets Ratio (CRAR), which is a similar ratio in banking system. Inclusion of further relevant independent variables may reveal further findings. We leave this for the future investigations. A causality test between the solvency and the financial stability as well as between the solvency and listed in the TSE is suggested for further investigation.

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