行政院國家科學委員會專題研究計畫 成果報告

模擬分析,情境分析,資本適足率,與風險基礎資本破產預 警能力之實證分析

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中文摘要

保險公司的財務健全度是保險監理的焦點,而普遍用來預防保險公司破產的方法是建立 最低資本額的要求。雖然現在的最低資本要求已經從固定的金額進展成風險基礎資本, 但文獻顯示風險基礎資本在提供破產預警方面的效力很低,目前效力最高的方法是以動 態現金流量模型所做的情境分析。由於情境分析的下一步就是模擬分析,本計畫的目的 就是檢驗模擬分析在破產預警方面的效力。

我們發現模擬分析與情境分析都比風險基礎資本更能正確地分類出財務健全/不健全的公司,只是模擬分析的效力與情境分析差不多。模擬分析並沒有更好的這個結果,可能是因為模擬分析與情境分析都是用同一個現金流量模型。

關鍵詞:模擬分析,情境分析,風險基礎資本,破產預測

Abstract

The solvency of the insurance company is the focal point of insurance regulation. One prevalent way to safeguard the insurer's financial strength is setting capital requirement. Although capital requirements have been transformed from constant ones to risk-based capital requirement (RBC), the literature finds that RBC is rather ineffective in rendering early warning. The literature to date further shows that scenario analysis done with dynamic cash flow models generates the best predicting results. Since a natural extension of scenario analysis is simulation analysis, this project aims to investigate the effectiveness of simulation analysis in solvency/insolvency predictions.

We find that simulation analysis as well as scenario analysis does dominate RBC in correctly classifying insurers' financial conditions. However, simulation analysis outperforms scenario analysis only by small or insignificant margins. Such a tie mainly results from the use of the same cash flow model.

Keywords: simulation analysis, scenario analysis, risk-based capital, solvency prediction

Insurer's solvency has always been the primary concern of insurance regulators and capital requirement is one of the most important elements in the supervision. employed capital requirement in the United States is risk-based capital (RBC). **RBC** was developed by National Association of Insurance Commissioners (NAIC) in responding to the concern of the U.S. Congress about the adequacy and accuracy of insurance solvency surveillance. Under RBC, each insurer must calculate the amount of capital required to support the company's total risk. An insurer's risk is assessed with several components such as asset risk and underwriting risk¹. Each component contains several risk factors corresponding to the insurer's activities that create risk. For instance, a property-casualty insurer's R2 risk is further decomposed into risk factors of common stocks, preferred stocks, real estate, schedule BA assets, receivables for securities, and aggregate write-ins for invested assets. A weight or a risk charge is assigned to each risk factor, and the product of the weight and the amount at risk (or positions) gives the amount of capital required to support the firm's activities associated with that risk factor. Aggregating these dollar amounts with pre-specified correlations among risk factors and risk components results in the authorized control level risk-based capital (ACLRBC) for the insurer². ACLRBC is then compared with the total adjusted capital (TAC) reported in the statutory financial statements. An insurer with TAC below certain multiples of its ACLRBC is deemed as inadequately capitalized and would receive regulator's special attention or action³. RBC went into effect in 1993 for life insurers and in 1994 for property-casualty insurers in the United States. Several other countries such as Taiwan and Singapore are going to implement RBC too.

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¹ NAIC (1999b) classifies the risks of property-casualty insurers into asset risk – subsidiary insurance companies (R0), asset risk – fixed income (R1), asset risk – equity (R2), asset risk – credit (R3), underwriting risk – reserves (R4), and underwriting risk – net written premiums (R5). For life insurers, the risks are categorized as asset risk – affiliates (C0), asset risk – other (C1), insurance risk (C2), interest rate risk (C3a), health credit risk (C3b), business risk excluding health administrative expense component (C4a), and health administrative expense component of business risk (C4b) (NAIC, 1999a). Please refer to *Risk-Based Capital Newsletter* of NAIC for the most updated revision.

² The formula of ACLRBC for life insurers is $0.5 \times (C0 + C4a + \sqrt{(C1 + C3a)^2 + C2^2 + C3b^2 + C4b^2})$, which implies that C1 and C3a are perfectly and positively correlated, C2, C3b, C4b, and the sum of C1 and C3a are independent of each other, and C0 and C4a are perfectly and positively correlated with the sum of the rest components. The ACLRBC for property-casualty insurers is $0.5 \times (R0 + \sqrt{R1^2 + R2^2 + R3^2 + R4^2 + R5^2})$, which implicitly assumes that R1 through R5 are not correlated with each other while the sum of these risks is perfectly and positively correlated with R0. Risk factors within the same risk component are assumed to be perfectly and positively correlated, since the required capital for a risk component is simply the sum of the required capital for individual risk factors in that component.

According to the NAIC's model legislation, the commissioner may take necessary actions to rehabilitate the company, including seizure or liquidation, when the insurer's TAC is less than ACLRBC. When TAC is between 1 and 1.5 times of ACLRBC, the commissioner may issue corrective orders to the company. When TAC is between 1.5 and 2 times of ACLRBC, the company must present a plan approved and monitored by its insurance commissioner to increase this ratio.

The effectiveness of RBC has been called into question by recent research, however. Cummins, Harrington, and Klein (1995) were the first to analyze the ability of RBC in predicting insurer's insolvencies. They found that the predictive accuracy of RBC was very low even when individual components of RBC were used as predictors. Grace, Harrington, and Klein (1998) (GHK) compared the predictive power of RBC with the Financial Analysis and Surveillance Tracking (FAST) audit ratio system. They also found that few companies that later failed had RBC ratios within the NAIC's ranges for regulatory actions. Furthermore, they found that FAST scores provided superior predictive power to RBC and RBC added no information to FAST. Cummins, Grace, and Phillips (1999) (CGP) extended GHK's papers in adding scenario analysis into the comparison list. They first confirmed that RBC and its components provided very low solvency predicting power. Also, RBC was dominated by FAST and a model containing FAST scores alone is as good at predicting insolvencies as a model with both FAST and RBC. Finally, scenario analyses performed with their cash flow simulation model dominated both RBC and FAST. The most recent paper, Pottier and Sommer (1999), confirmed again that RBC ratio was a poor predictor of insolvencies and then showed that the Best Capital Adequacy Ratio (BCAR), a risk-based capital system developed by A. M. Best Company, was more accurate. In summary, the insurance literature found that the solvency prediction ability of RBC was worse than that of a private sector's risk-based capital ratio (BCAR), another regulatory measure (FAST), and scenario analysis.

The published papers to date indicate that scenario analysis generates the best solvency predictions. The superior performance of scenario analysis over RBC could be due to two reasons: full valuation and dynamic analysis⁴. RBC is a local valuation method that is linear fundamentally, since the potential loss in a portfolio's value V is computed as $\Delta V = V_0 \times \beta_0 \times \Delta P$, where β_0 is the portfolio's sensitivity to changes in prices evaluated at the current position $\,V_0\,$ and $\,\Delta P\,$ is the potential change in prices $^5.\,$ Linear approximation is valid only for a narrow range of price movements. Furthermore, a portfolio's sensitivity to price changes might change with price movements and might even be different for up and down moves. Solvency testing by its nature, however, would involve large and asymmetric price movements over a period of time. RBC hence is handicapped. On the other hand, scenario analysis examining the effect of simulated large movements in key financial variables on the portfolio is a full valuation approach that directly computes the value of the

⁴ A third possible reason is that the risk charges specified in RBC are simply bad. ⁵ Hence, risk charges in RBC = $\beta_0 \times \Delta P$.

portfolio for different levels of prices: $\Delta V = V(P_1) - V(P_0)$, which should be more accurate. The second advantage of scenario analysis is its dynamic nature. Scenarios analysis usually is performed with a dynamic cash flow model that projects the company's financial positions over a period of time, while RBC uses only the company's financial positions at a point of time. Ignoring the potential variations in the compositions of the asset and business books further impair the risk measurement accuracy of RBC.

Scenario analysis nevertheless has its own drawbacks. First, the specified scenarios are judgmental and the random aspects of variables are limited. In addition, scenario analysis does not specify the likelihood of worst-case situations. Furthermore, scenario analysis handles correlation, an essential component of a portfolio's risk, poorly. Finally, looking at extreme movements may not be appropriate because some positions (e.g. a long straddle position) lose most money when the underlying variables do not move at all.

A natural extension of scenario analysis is simulation analysis. Although simulation analysis still has certain subjectivity in the choice of stochastic models, it avoids the subjective specification on scenarios and allows complete randomness of variables. It generates thousands of scenarios including not only extreme scenarios but also median ones by the assumed probability distributions of underlying risk factors. Furthermore, simulation analysis could fully account for correlations among variables. Despite of its intensive demand on systems infrastructure and intellectual development, simulation analysis is by far the most powerful method in assessing risk (Jorion, 2001, p. 225).

The purpose of this project is to empirically test whether simulation analysis generates better solvency/insolvency predictions than scenario analysis and RBC do in the property-casualty insurance industry. We first build up a dynamic cash flow model for the property-casualty insurance company under certain valuation models. Scenario analysis can then be done. Further making the cash flow model random by introducing several stochastic risk models enables us to perform simulation analysis. We employ the value at risk (VaR) of the resulted insurer's surplus distribution as the output of our simulation analysis. VaR, scenario output, and RBC are then examined individually as well as in conjunction with others to measure their incremental predicting power. We use the data of property-casualty insurers up to 1994, 1995, 1996, or 1997 as the input to predict insurers' solvencies/insolvencies in 1996, 1997, 1998, and 1999 respectively. In other words, we empirically test the relative two-year early warning capabilities of simulation analysis, scenario analysis, and RBC on the insurers for the period from 1996 to 1999, by using the data two years earlier. The two-year early warning period is chosen because of the time lag

involved in preparing annual statements, analyzing the statements, and taking actions in a prescriptive manner. To make the model suitable for practical regulatory uses, most input of the model is from the NAIC annual statements.

We find that RBC falls behind simulation as well as scenario analysis with significant margins. In the univariate test, RBC has the lowest hit ratio. Furthermore, its type I error rates are the highest in general, even when the required ratio is raised significantly. In multivariate tests, the equation with RBC as the sole capital requirement variable fits the solvency/insolvency record the worst and its prediction results are also the worst. Moreover, RBC does not improve the fitting and the predicting power of the models containing scenario or VaR variables. We hence conclude that RBC is not as effective as scenario or simulation analysis in predicting insurers' solvencies/insolvencies.

With regard to the relative effectiveness between scenario and simulation analysis, we first find from the univariate test that VaR generates a little bit better prediction accuracy than scenario variables. VaR has higher hit ratio in general. The multivariate tests however show that VaR and scenario variable have close fitting statistics and predicting power. Therefore, we do not find significant superiority of simulation over scenario analysis in solvency/insolvency predictions, when both analyses are done with the same dynamic cash flow model.

The improvement of simulation analysis over RBC in fact should be more than what this paper has shown. First, the cash flow model developed in this project is still preliminary. For instance, it misses an important aspect of property-casualty insurance operation, reinsurance. Refining the cash flow model would result in more accurate risk profiles. Second, we use industry data instead of company data in many cases, especially with the assets, due to the lack of data. Using more company data would certainly enhance the model's differentiating ability. Third, some parameters in the model are estimated with very limited amount of data, especially parameters of loss distributions. More loss development data would help to correctly profile insurer's underwriting risk. Therefore, simulation analysis could outperform RBC by an even larger margin and insurance regulators should seriously consider employing such analyses in determining capital requirements for property-casualty insurers.

References

Cummins, J. David, Martin F. Grace and Richard D. Phillips, 1999, Regulatory Solvency

- Prediction in Property-Liability Insurance: Risk-Based Capital, Audit Ratios, and Cash-Flow Simulation, *Journal of Risk and Insurance*, 66: 417-458.
- Cummins, J. David, Scott E. Harrington, and Robert Klein, 1995, Insolvency Experience, Risk-Based Capital, and Prompt Corrective Action in Property-Liability Insurance, *Journal of Banking and Finance*, 19: 511-527.
- Grace, Martin F., Scott E. Harrington, and Robert Klein, 1998, Risk-Based Capital and Solvency Screening in Property-Liability Insurance: Hypotheses and Empirical Tests, *Journal of Risk and Insurance*, 65: 213-243.
- Jorion, Philippe, 2001, Value at Risk: The New Benchmark for Managing Financial Risk (Taipei, Taiwan: McGraw-Hill Companies, Inc.).
- NAIC, 1999a, Life Risk-Based Capital Report Including Overview and Instructions for Companies (Kansas City, MO: NAIC).
- NAIC, 1999b, Property and Casualty Risk-Based Capital Report Including Overview and Instructions for Companies (Kansas City, MO: NAIC).
- Pottier, Steven W. and David W. Sommer, 1999, Capital Ratios and Property-Liability Insurer Insolvencies, Working Paper (presented in 1999 ARIA annual meeting), University of Georgia, Athens, Georgia.