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Article

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Evaluation of Target Deposit Insurance Fund Based on Credit Migration Approach for the Non-Life Insurance Sector in Korea

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A B S T R A C T

Purpose: In the case of non-life insurance business, the rate for the accumulation of fund in non-life insurance has fallen every year, making it difficult to reach the target fund level. Thus, we evaluate the appropriate target fund level for non-life insurers.

Design/methodology/approach: The portfolio of the deposit insurer was constructed for 21 non-life insurers which were licensed non-life insurance businesses under the Insurance Business Act 4 (1) in Korea. We attempt to analyze the default probability using the Credit Migration method rather than the Merton. We derive the joint distribution for change in credit ratings and a loss distribution of the deposit insurer in non-life insurance sector by performing the Monte-Carlo simulation. The average value of the worst loss with a 0.5% probability in the loss distribution, $TVaR_{99.5\%}$, was adopted as an appropriate target fund level.

Findings: The value of $TVaR_{99.5\%}$ in this study was between 67 billion won and 2.434 trillion won. This amount of money is from 4.71% to 171.71% of the current deposit insurance fund for non-life insurers, and from 4.06% to 147.52% of the target fund level for non-life insurers. However, if a rather extremely conservative case that reflects the loss of deposit insurance funds due to the bankruptcy of up to 7 insurers among non-life insurers that consists of the portfolio is excluded, the distribution of the $TVaR_{99.5\%}$ was between 67 billion won and 402 billion won. This money is from 4.71% to 28.28% of the current deposit insurance fund, and from 4.06% to 24.37% of the target fund level for non-life insurers. These results indicate that additional funding is unnecessary because the current level of deposit insurance funds will sufficiently cover future losses.

Research limitations/implications: The limitation of this study is to evaluate the deposit fund under the RBC system, since it is controversial whether the RBC system adequately reflects the risk of non-life insurers. The risk of minimum guaranteed interest rate, catastrophe risk and liquidity risk are needed to be considered through further study. In particular, comparing the loss distribution for individual insurers under Solvency II and the RBC system is a future task of research.

Originality/value: This study contributes to the evaluation of the target deposit insurance fund for non-life insurers by applying the credit migration method unlike the existing studies. This attempt is meaningful in that it provides an objective and practically easy-to-use alternative to the market participants such as the deposit insurer and non-life insurers.

Keywords: Deposit insurance system, Credit migration, Non-life insurers, TVaR, Target fund

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I. Introduction

The deposit insurance system protects depositors by providing insurance for deposits and prevents bank runs, thereby contributing to the stability of the financial market in the case of a failure of the financial institutions. Each country has a different deposit insurance system with a different scope of regulated financial institutions and coverage, depending on its economic situation, such as the level of financial development and regulatory environment. In Korea, the government operates a single deposit insurance system including banks, insurance companies and other financial institutions, while most countries operate a separate insurance system to protect policyholders. However, it is controversial whether the single deposit insurance system is appropriate because the liabilities of the insurer are very different from those of banks, as well as the fact that the regulations for capital adequacy applied to each financial industry are also very different. Among other things, the most controversial subject is the appropriate level and methodology applied to calculate the target fund. This is because an excessive level of target fund reduces the efficiency of the financial industry, whereas lack of target fund reduces the credibility in the financial systems. O`keefe and Ufier (2017) also point out that the method to calculate the target fund and level of the fund should be reviewed regularly for validity as financial conditions change. In this regard, this study aims to examine alternative ways of evaluating an appropriate target fund focusing on non-life insurers.

Since Diamond and Dybvig (1983) show that a Pareto-inferior equilibrium such as a bank run can be averted into a better equilibrium by government controlled deposit insurance system and the suspension of convertibility in deposits, many studies have investigated the role of deposit insurance, the effect of deposit insurance on financial stability, optimal coverage with moral hazard of depositors and optimal insurance premiums and target funds. Among the vast literature, as noted above, we focus on the studies for the evaluation of target funds.

The most widely used method in the evaluation of the target fund is based on the corporate bond pricing model of Merton (1974). The asset value and the variance of asset return are calculated from stock market information. The probability that liability is greater than asset value is regarded as default value and the probability can be obtained using the Black-Scholes option pricing framework. The model based on Merton (hereafter the Merton model) has the advantages of using market information and being forward looking. The market information such as the stock price reflects the results evaluated in real time by market participants, so it is the fastest and most accurate information that shows the current level of the firm. However, the companies with market information are limited to listed companies and the nature of the option model, by assuming no arbitrage condition and an efficient market, limits the advantages of the model. In addition, the probability that an asset is less than a liability does not indicate the default probability, but the equity impairment probability. This implies that the default probability of the Merton model tends to overestimate the real default probability. To improve the problems of the Merton model, the KMV-Merton model, developed by KMV for credit analysis, is used in both real world and academic research based on the Merton model. Even though the KMV-Merton model adjusts the default distance of the Merton model, the KMV-Merton model is similar to the Merton model.

However, some studies still point out that the KMV-Merton model cannot reflect the characteristics of each firm and industry. In particular, Won and Choi (2006) point out that in the KMV-Merton model, the probability of default prediction is not high for the companies with a certain level of potential for equity impairment. Bharath and Shumway (2004) and Kim (2009) argue that the default probability from KMV-Merton model is not a sufficient statistic to predict default. Kim (2009) examines the target fund for non-life insurers in Korea based on the KMV-Merton model. He finds that the volatility of asset value, which is the key factor to estimate the model, is not stable. In addition, Jeong et al. (2002)

attempt to predict the change in credit risk using both the KMV-Merton model and implied default rate (IDR). They pointed that the default probability calculated through the KMV-Merton model has a limitation that the volatility is too high compared to IDR. Lee and Kim (2015) compare the predictability for default probability of non-financial companies listed in Korea between accounting model, the KMV-Merton model and a modified hazard model. They show that the modified hazard model has the highest default prediction. These studies point out that the default probability based on the KMV-Merton model needs to be carefully reviewed and interpreted, and also point out the accuracy of estimating the default probability for financial institutions. Accordingly, studies using other approach rather than the KMV-Model are being introduced to estimate the default probability. Choi et al. (2017) point out that the KMV-Merton model has the disadvantage of not being able to control the effects of macroeconomic, industrial and temporary factors on the stock price, and used text mining and artificial intelligence techniques to estimate the probability of better default probability. Olarewaju and Salako (2020) use CDS premium to estimate default probability.

In recent times, there are a few studies on the evaluation of target fund. For example, O'keefe and Ufier (2017) suggest the methodology for determining the target deposit insurance fund. Chun and Oh (2018) investigate the interconnectedness of financial institutions in Korea using the Principal Component Analysis (PCA). They conclude that the current level of deposit insurance fund is not sufficient, particularly in the sector of savings banks and special account. Lee et al. (2019) estimate the deposit insurance fund for savings banks using a scenario analysis and point out the deficit of the fund.

In this study, we attempt to analyze the default probability for non-life insurers through the credit migration method rather than the Merton (or the KMV-Merton) model. Unlike the Merton model, which is based on a rather strong assumption of efficient market and no-arbitrage condition, the credit migration model has the advantage that the default probability can be easily estimated based on the observable data such as credit ratings. The credit migration method is to use objective data such as credit ratings and the probability of change in credit ratings that are easily available and to estimate the future distribution for the change in portfolio value and the maximum expected loss under given confidence level. In this study, the portfolio indicates the deposit insurance fund for non-life insurers. In addition, the credit migration method allows us to evaluate the entire portfolio risk as well as the diversification effect of risk in portfolio because this method incorporates the correlation between non-life insurers into the evaluation model. That is, when using the credit migration method to evaluate the target fund for non-life insurance industry, it is possible to estimate the appropriate target fund level within a consistent analysis framework as well as to determine the deposit insurance rate in further studies. We derive the joint distribution of change in credit ratings and loss distribution for the portfolio through Monte Carlo simulations based on the credit ratings issued by domestic credit rating agencies and the S&P. In addition, we evaluate the target fund level at $TVaR_{99.5\%}$ and compare the current deposit insurance fund and the level of $TVaR_{99.5\%}$.

The remainder of this paper is organized as follows. In Section 2, we summarize the procedures of the credit migration method. In Section 3, we describe the characteristics of data and model assumptions. In Section 4, we evaluate the target deposit insurance fund for non-life insurers. In Section 5, we conclude.

II. Credit Migration Method

The credit migration method is initiated by JP Morgan (1997). It is difficult to observe the market value and volatility of the value for assets such as debt and bonds not traded on the market. JP Morgan develops CreditMetrics to measure the credit risk of these assets using the information of the credit

rating of debtors, the probability of change in credit rating, recovery rate and credit spread in debt market. From the historical information of the change in credit ratings, the joint distribution of the change in credit ratings within a given time horizon (for example, 1 year or 3 years) which implies that the probability of moving from one credit rating to another is estimated. CreditMetrics supposes that the changes in value are normally distributed. Similarly, threshold can be estimated for transitions to other rating states. The change in credit rating leads to the change in credit risk itself and credit premium corresponding to the rating changes as well. Consequently, the market value of debt or bond is changed. The elements of the transition matrix provide a methodology to simulate the change in credit rating. Given a set of transition probabilities in each credit rating, the critical distances can be calculated in each category of rating. For a portfolio of credits, the changes in underlying asset values can be simulated.

The credit migration approach is used in several studies. Altman and Kao (1992) and Helwege and Tumer (1999) analyze the default risk of corporate issuers based on the credit migration method. Bangia et.al (2002) state that credit migration method provides the linkages between underlying macroeconomic conditions and asset quality. They also show that the loss distribution of credit portfolio based on the credit migration method can differ between two economy states: expansion and contraction. Schuermann (2014) calculate the value distribution for a credit asset portfolio using credit migration method. Tsaig et al. (2011) show that the credit migration can explain 51% of volatility and 35% of economic capital in a typical loan portfolio. In line with these studies, we adopt credit migration approach to evaluate the target fund.

The procedure for the credit portfolio method consists of the following three steps: At first, it was needed to measure the credit exposure amounts of individual assets within a portfolio. Second, the volatility of asset values were measured through the changes in credit ratings of individual assets and credit spreads and the recovery rates based on the credit. In the last stage, the value of the entire portfolio was calculated by considering the correlation between individual assets. The distribution of portfolio value changes taking into account all changes occurring over time could be estimated from this three-step process using Monte-Carlo Simulation techniques.

In this study, the credit migration method was applied to analysis using the above credit portfolio method. We evaluated the target fund of non-life insurers through the following steps: First, a portfolio was constructed for 21 non-life insurers which were licensed non-life insurance businesses under the Insurance Business Act 4 (1). Next, using the required capital of Risk Based Capital (RBC, hereafter) regulation, the distribution (normal distribution) of the loss amount was derived for each non-life insurer. The RBC regulation categorizes risks inherent in insurers into the following: insurance risk, interest risk, credit risk, market risk, and operating risk. The determinants of each risk and the specific meanings are summarized in Table 1 below. The RBC required capital is defined as the difference between the expected maximum loss and average loss by considering the above 5 risks at the time of analysis. Note that this amount of capital indicates VaR under the confidence level of 99%. Thus, using the required capital of individual non-life insurers, the distribution of unexpected loss over a year can be estimated. Lastly, to derive the joint distribution for the change in credit rating of the portfolio which consists of non-life insurers, we considered the correlation between the default probabilities of the target non-life insurers. The correlation between the market capitalization of non-life insurers was used as a proxy for the correlation of the default probability. Market capitalization is appropriate to use as a proxy for the default probability because it reflects the future firm value and thus, it is positively correlated with the default probability. Meanwhile, in this study, the correlation of market capitalization was substituted by the average value of correlation for the listed companies because the correlation between unlisted companies could not be obtained.

We have the loss distribution for non-life insurers

Table 1. Definitions and determinants of individual risks

Classification	Definition	Determinant
Insurance risk	Risk of loss due to unexpected increase in loss ratio	· Loss ratio · Reserve level
Interest risk	Risk of fluctuating interest rates that will have a negative impact on the financial position	· Asset/Liability duration · The proportion of interest-linked products
Credit risk	Risk of loss arising from the default of the debtor and default of the counterparty	· Asset credit rating · Credit enhancement such as collateral
Market risk	Risk of loss due to changes in market prices (stock price, interest rate, exchange rate, etc.)	· Appropriateness of diversified investment
Operational risk	Risk of loss due to improper internal procedures, personnel, systems, or external events	· Appropriateness of internal control

Source: RBC commentary for insurance company. FSS (2017)

and the current level of deposit insurance fund for non-life insurers through the Monte-Carlo simulation based on the results of the process noted above. In this study, we chose the average amount of the worst loss ($TVaR_{99.5\%}$) with a 0.5% chance of loss distribution as the basis for the evaluation of the level of the fund for non-life insurers. This is because it would be more appropriate to choose TVaR, which implies the average value of an unexpected maximum loss rather than to choose VaR, which implies the minimum value of an unexpected maximum loss, considering long and thin tail of loss distribution from a conservative point of view.

III. Data and Model Assumptions

In this section, we explain the data and assumptions used to analyze the level of the target fund for non-life insurers. As aforementioned, 21 non-life insurers subject to deposit insurance were targeted as of the end of 2019. The credit ratings for empirical analysis were obtained from "Insider Financial Strength Rating" or "Issuer Rating" approved by domestic and international credit rating agencies. Of the 21 insurers analyzed, eight insurers were rated only by domestic agencies, but not rated by an international credit rating agency (S&P). Seven insurers were rated by S&P, but not rated by domestic agencies. In this case, we transformed the rating data based on the "Regulations for Implementation of Supervision of Insurance Business" as given below. Two have neither domestic ratings nor international ratings. We conservatively applied the lowest rating among the insurers analyzed to these two companies. The following Table 2 summarizes the credit ratings for 21 non-life insurers.

The probability of change in credit ratings was one of the most essential data for this empirical analysis. We used the average probability in the probability of change in credit ratings within a year provided by two domestic rating agencies and S&P (2019). Note that the probability indicates the possibility to use the fund for non-life insurers as the default occurs. The probabilities are in the following tables (See Tables 3 and 4).

Since most of the non-life insurers with large market shares in the overall non-life insurance market of Korea are rated by domestic agencies, it was reasonable to apply the credit ratings by domestic agencies to measure the probability of change in credit ratings in principle for this study. However, due to insufficient data of domestic agencies, the default probability of non-life insurers with a high rating (AA- or higher) may be underestimated in case when using that probability generated by domestic agencies. In addition, there existed a limitation in that the difference in probability of each credit rating group was not reflected because domestic agencies did not provide the probability of change in credit

Table 2. Credit ratings of non-life insurers

Non-life insurers	Effective credit rating		Applied credit ratings	
	Credit ratings by domestic agencies	Credit ratings by S&P	Credit ratings by domestic agencies	Credit ratings by S&P
Samsung	AAA	AA-	AAA	AA-
Hyundai	AAA	A-	AAA	A-
DB	AAA	A	AAA	A
KB	AA+	N/A	AA+	A+
Meritz	AA+	N/A	AA+	A+
Hanhwa	AA-	N/A	AA-	A-
Heunguk	A+	N/A	A+	BBB+
Lotte	A+	N/A	A+	BBB+
NH	AA-	N/A	AA-	A-
MG	A-	N/A	A-	BBB-
Hana	A-	N/A	A-	BBB-
Carrot	N/A	N/A	A-	BBB-
AXA	N/A	AA-	AAA	AA-
AIG	N/A	A+	AA+	A+
ACE	N/A	AA	AAA	AA
Mitsui Sumitomo	N/A	A+	AA+	A+
BNP Paribas	N/A	A+	AA+	A+
First American	N/A	A-	AA-	A-
Das	N/A	N/A	A-	BBB-
Allianz	N/A	AA	AAA	AA
SGI	AAA	A+	AAA	A+

Note: If there is no valid credit rating (N/A), it is converted and applied according to the credit rating conversion table.

Table 3. Distribution of probability of change in credit ratings by domestic credit rating agencies (1 year)

(Unit : %)

		Credit ratings after 1 year						
		AAA	AA	A	BBB	BB	B or lower	D
Initial credit ratings	AAA	99.62	0.38	0.00	0.00	0.00	0.00	0.00
	AA	0.96	96.56	2.37	0.10	0.00	0.00	0.00
	A	0.00	5.69	90.23	3.56	0.16	0.31	0.06
	BBB	0.00	0.00	7.75	85.80	3.89	2.10	0.45
	BB	0.00	0.00	0.29	6.42	77.09	10.15	6.05
	B or lower	0.00	0.00	0.00	0.43	3.31	82.83	13.43

ratings in each rating group. On the contrary, S&P provided the probability of change in credit rating for each rating group as well as the higher default probability within the same credit rating firms compared to the domestic agencies so that let us maintain the more conservative basis (See Table 5). Therefore, we evaluated the target fund by applying the probability data of domestic agencies and S&P for comparison.

We also analyzed the target fund of non-life insurers using the probability of change in credit ratings within 3 years as well as that probability within 1 year. The target fund increases on a 3 year basis rather than a 1 year basis. Note that the probability within 3 years can be generated by multiplying the probability matrix for 1 year 3 times under the assumption that the changes in credit ratings within 1 year are mutually independent, occur 3 times sequentially and follow a Markov process (See Tables 6 and 7).

In the meanwhile, it is reasonable to assume that

Table 4. Distribution of probability of change in credit ratings by S&P (1 year) (Unit: %)

		Credit ratings after 1 year											
		AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	…	D
Initial credit ratings	AAA	87.03	5.89	2.51	0.69	0.16	0.24	0.13	0.00	0.05	0.00	…	0.00
	AA+	2.31	78.94	10.91	3.54	0.71	0.33	0.19	0.05	0.09	0.05	…	0.00
	AA	0.42	1.31	80.76	8.53	2.72	1.15	0.36	0.39	0.13	0.08	…	0.02
	AA-	0.04	0.11	3.77	78.80	9.68	2.19	0.60	0.25	0.15	0.07	…	0.03
	A+	0.00	0.06	0.44	4.44	78.38	8.73	2.15	0.61	0.34	0.09	…	0.05
	A	0.03	0.04	0.22	0.41	5.32	78.88	6.74	2.38	0.86	0.27	…	0.05
	A-	0.04	0.01	0.06	0.15	0.42	6.49	78.12	7.23	1.98	0.57	…	0.06
	BBB+	0.00	0.01	0.05	0.06	0.20	0.74	7.13	75.83	7.98	1.56	…	0.10
	BBB	0.01	0.01	0.04	0.03	0.10	0.31	1.00	7.73	76.00	6.11	…	0.16
	BBB-	0.01	0.01	0.02	0.04	0.06	0.14	0.25	1.17	9.31	72.40	…	0.25
	…	…	…	…	…	…	…	…	…	…	…	…	…
	C	0.00	0.00	0.00	0.00	0.03	0.00	0.08	0.05	0.08	0.05	…	27.08

Table 5. Comparison of default probability (1 year)

Credit rating agency	S&P credit rating		
	AA(AAA)	A(AA)	BBB(A)
S&P	0.02%	0.05%	0.16%
KIS rating	0.00%	0.00%	0.05%
Other domestic rating agency	0.00%	0.00%	0.06%

Note: The rating in the parenthesis indicates the credit rating by domestic credit rating agencies.

Table 6. Distribution for the probability of change in credit ratings by Korea Credit Rating companies (3 years) (Unit : %)

		Credit ratings after 3 year						
		AAA	AA	A	BBB	BB	B or lower	D
Initial credit ratings	AAA	98.89	1.09	0.03	0.00	0.00	0.00	0.00
	AA	2.78	90.44	6.24	0.49	0.02	0.03	0.01
	A	0.16	14.92	74.57	8.34	0.71	0.94	0.37
	BBB	0.00	1.20	18.09	64.54	7.99	5.54	2.63
	BB	0.00	0.07	1.88	12.97	47.22	19.88	17.97
	B or lower	0.00	0.00	0.13	1.44	6.41	57.67	34.35

the changes in credit ratings of non-life insurers are related to each other rather than mutually independent. That is, it is necessary to estimate the correlation between changes in credit ratings of individual insurers to reflect how a change in one insurer's credit rating affects the credit ratings of other insurers or the entire non-life insurance industry. It is common practice to derive a joint distribution of changes in the credit ratings by using correlations of stock prices or market capitalization in case the companies are listed. In this study, the covariance matrix derived from the time series data of market capitalization of non-life insurers was applied as a proxy for the covariance matrix of the changes in credit ratings. Since the covariance for 13 unlisted insurers could not be calculated, the average value of the covariance for 8 listed insurers substituted the covariance for unlisted insurers.

The evaluation of target fund for non-life insurers was conducted by the Monte-Carlo Simulation method. Thus, the covariance matrix should be positive definite to properly generate the scenario for changes in credit ratings without the distortion of distribution with regard to changes in credit ratings for the portfolio composed of 21 non-life insurers. In other words, all eigen-values of the covariance matrix should be positive. However, this condition was not satisfied because the correlations for 13 unlisted insurers were

Table 7. Distribution for the probability of change in credit ratings by S&P (3 years) (Unit : %)

		Credit ratings after 3 year											
		AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	…	D
Initial credit ratings	AAA	72.88	13.47	7.72	2.82	0.96	0.83	0.44	0.11	0.16	0.04	…	0.05
	AA+	5.37	54.46	23.64	9.97	3.34	1.54	0.72	0.35	0.30	0.16	…	0.02
	AA	1.09	2.91	60.77	18.99	8.35	3.85	1.43	1.14	0.52	0.27	…	0.12
	AA-	0.15	0.39	8.37	57.69	21.19	7.23	2.41	1.07	0.61	0.26	…	0.12
	A+	0.03	0.17	1.49	9.69	57.70	19.38	6.39	2.42	1.27	0.42	…	0.17
	A	0.08	0.11	0.63	1.61	11.61	58.80	15.19	6.61	2.88	0.99	…	0.19
	A-	0.10	0.04	0.21	0.49	1.92	14.11	57.16	15.83	6.03	1.93	…	0.25
	BBB+	0.01	0.03	0.15	0.22	0.69	2.95	15.27	54.44	17.33	4.70	…	0.42
	BBB	0.03	0.03	0.12	0.12	0.35	1.10	3.75	16.53	56.11	13.20	…	0.62
	BBB-	0.03	0.03	0.07	0.12	0.21	0.50	1.12	4.51	19.67	50.67	…	1.10
	…	…	…	…	…	…	…	…	…	…	…	…	…
	C	0.00	0.00	0.00	0.01	0.06	0.04	0.15	0.14	0.19	0.16	…	59.84

Table 8. Covariance matrix for market capitalization

	Samsung	Hyundai	DB	KB	Meritz	Hanhwa	Heungkuk	Lotte	Others
Samsung	1.0000	0.3217	0.5084	-0.2083	-0.0943	0.3680	0.1752	-0.2260	0.3021
Hyundai		1.0000	0.0542	0.6930	0.7070	0.7942	0.7555	0.3112	0.3021
DB			1.0000	-0.4871	-0.0482	0.0367	-0.2737	0.0414	0.3021
KB				1.0000	0.7590	0.5388	0.7511	0.3359	0.3021
Meritz					1.0000	0.4245	0.6710	0.4399	0.3021
Hanhwa						1.0000	0.7056	0.2096	0.3021
Heungkuk							1.0000	0.1942	0.3021
Lotte								1.0000	0.3021
Others									1.0000

Table 9. Covariance matrix for market value satisfying positive-definite condition

	Samsung	Hyundai	DB	KB	Meritz	Hanhwa	Heungkuk	Lotte	Others
Samsung	1.0170	0.3056	0.5327	-0.1773	-0.0962	0.3676	0.1843	-0.2126	0.2973
Hyundai		1.0153	0.0311	0.6636	0.7088	0.7946	0.7469	0.2984	0.3067
DB			1.0348	-0.4428	-0.0510	0.0361	-0.2607	0.0606	0.2952
KB				1.0565	0.7555	0.5380	0.7677	0.3604	0.2933
Meritz					1.0002	0.4245	0.6700	0.4384	0.3026
Hanhwa						1.0000	0.7054	0.2093	0.3022
Heungkuk							1.0049	0.2014	0.3000
Lotte								1.0106	0.2983
Others									1.0014

assumed to be the average value (See Tables 8 and 9). We generated the covariance matrix satisfying positive definite condition by applying the method of Schaeffer (2014) without significantly undermining the information of covariance matrix for market capitalization. Note that Schaeffer (2014) suggests a method of converting the matrix to be positive definite if the covariance matrix is singular and thus, the matrix cannot be inverted. The procedure is as follows. At the first step, the negative eigenvalues are summed, multiplied by 2. Let us denote this value as s. Next, the value t is obtained by multiplying s by 100 and adding 1. At the last step, the new eigenvalue is obtained based on the following formula: $n = p \times (s-n)^2/t$, where p is the lowest positive eigenvalue. This method does not significantly undermine the negative eigenvalues and converts them into positive eigenvalues.

The data such as credit ratings, probability of changes in credit ratings and market capitalization were needed to measure the default probability of the target non-life insurers, that is, the frequency of deposit insurance funds used by the target non-life insurers. On the other hand, the RBC required capital data was needed to calculate the amount of deposit insurance fund in the case when the target insurers default. The RBC required capital is defined as a difference between the expected maximum loss value within a year and the average loss value considering the 5 risks in Table 1 (See Table 10). The RBC required capital is appropriate to measure the deposit insurance fund loss in that the RBC required capital reflects the characteristics of non-life insurance well. We

Table 10. RBC required capital and the volatility of loss distribution (Unit : million won)

Non-life insurance company	RBC required Capital	Volatility of loss distribution
Samsung	4,645,516	1,996,914
Hyundai	2,594,897	1,115,438
DB	3,102,193	1,333,503
KB	1,940,678	834,217
Meritz	1,692,337	727,465
Hanhwa	1,094,838	470,625
Heungkuk	611,454	262,839
Lotte	734,786	315,854
NH	445,919	191,682
MG	213,075	91,592
Hana	82,202	35,335
Carrot	1,551	667
AXA	102,988	44,270
AIG	75,073	32,271
ACE	60,986	26,215
Mitsui Sumitomo	15,707	6,752
BNP Baribas	9,403	4,042
First American	5,657	2,432
Das	64	28
Allianz	13,948	5,996
SGI	1,159,694	498,504

Note: The volatility is calculated by required capital based on RBC / $Z_{99\%}$.

estimated the distribution of unexpected loss for each non-life insurer within a year from the basis time of December 2019. We also estimated the loss of deposit insurance fund from the default using this distribution.

IV. Evaluation of the target fund for non-life insurers

In this section, we performed the Monte-Carlo simulation using the data and assumptions described above and derived a joint distribution for changes in credit ratings and a loss distribution for the portfolio. Since the default probability of individual non-life insurer was very low, we generated 100, 000 scenarios and simulated in order to ensure the statistical stability of our analysis. Recall that in this study, the average value of the worst loss with a 0.5% probability in the loss distribution was adopted as an appropriate target fund level. The joint distributions for changes in credit ratings according to 100,000 simulations for the above cases (See Table 11) are represented in the following Table 12. Note that even 1,000 and 10,000 simulations are more common, we adopt 100,000 simulations to obtain a reliable average value for TVaR99.5%. More simulations may be considered to improve accuracy, but 100,000 simulations are implemented considering computing times and efficiency. The confidence level of 99.5% implies the loss size equivalent to 1.11 times higher than the confidence level for RBC required capital, 99%, under the assumption of normal distribution. In addition, we evaluated the target fund for non-life insurers according to four cases in Table 11 by applying different distributions for the changes in credit ratings.

The joint distributions for changes in credit ratings according to 100,000 simulations for the above cases are represented in the following Table 12. In case I, the probability that one or more non-life insurers defaulting was 0.378%, which is very low. This is because 15 of the 21 insurers in the portfolio were rated AA- or higher by domestic agencies, and the default probabilities within a year for these insurers were zero. That is, the insurers with AA- or higher credit ratings did not contribute to the default probability of the overall portfolio under the joint distribution for the changes in credit ratings. However, even if an insurer's credit rating was very high, the default probability within a year was not zero. Thus, this result needs to be interpreted carefully as a benchmark case.

In case II, the probability of one or more non-life insurers defaulting is 1.514%, 4.01 times higher than that of case I. Unlike case I, all non-life insurers contributed to the default probability of portfolio under the joint distribution because the insurers did not have a 0% default probability within a year. In addition, since the overall default probabilities for each insurer were set higher than those of case I, the result can be regarded as a more conservative one and reflects the likelihood of default for all insurers.

In case III, the probability that one or more insurers

Table 11. Summary of 4 cases

Cases	Conditions
Case I	· Based on the credit ratings by domestic credit rating agencies · Applying credit migration probability (1 year)
Case II	· Based on the credit ratings by S&P · Applying credit migration probability (1 year)
Case III	· Based on the credit ratings by domestic credit rating agencies · Applying credit migration probability (3 years)
Case IV	· Based on the credit ratings by S&P · Applying credit migration probability (3 years)

Table 12. Joint probability distribution of credit rating migration (Unit : %)

Number of defaults	Case I	Case II	Case III	Case IV
0	99.622	98.486	97.905	94.862
1	0.370	1.341	1.925	4.230
2	0.008	0.137	0.149	0.607
3	0	0.028	0.018	0.211
4	0	0.008	0.002	0.064
5	0	0	0.001	0.013
6	0	0	0	0010
7	0	0	0	0.002
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0
11	0	0	0	0
12	0	0	0	0

0.378 (Case I, 1–7) | 1.514 (Case II, 1–7) | 2.095 (Case III, 1–7) | 5.137 (Case IV, 1–7)

Table 13. Evaluation of deposit insurance fund for non-life insurers (Unit : %, million won)

	Case I	Case II	Case III	Case IV
Probability of using deposit insurance fund	0.378%	1.514%	2.095%	5.137%
$TVaR_{99.5\%}$	66,987	606,979	402,073	2,434,061
(Proportion to fund)	(4.71%)	(42.69%)	(28.28%)	(171.17%)
(Proportion to target)	(4.06%)	(36.82%)	(24.37%)	(147.52%)

Note: The proportion of fund denotes the proportion of $TVaR_{99.5\%}$ to deposit insurance fund for non-life insurers. Similarly, the proportion of target denotes the proportion of $TVaR_{99.5\%}$ to target deposit insurance fund for non-life insurers.

defaulting was 2.095%, 5.54 times higher than that of case I. In case IV, which follows the most conservative basis, the probability that one or more insurers defaulting was 5.137%, 13.59 times higher than case I. Note that this value reflects the loss of deposit insurance fund from up to seven of the insurers in the portfolio.

The loss distribution of the portfolio can be generated as the sum of the losses extracted from the loss distribution of an individual insurer in the case of default. The results are as follows: In case I, $TVaR_{99.5\%}$ on the loss distribution of the portfolio was 67 billion won. The amount of the deposit insurance fund for non-life insurers was 1.42 trillion won in 2019 and our estimate was only 4.71% of the fund. Furthermore, the lower limit set by the deposit insurer was 1.65 trillion, 24.64 times higher than the estimate obtained in this study. Note that this result came from setting a 0% loss probability for 15 of the insurers. $TVaR_{99.5\%}$ in case II on the loss distribution of the portfolio was 607 billion won. This amount is 42.69% of the deposit insurance fund for non-life insurers in 2019. If case II becomes the criterion of target fund for non-life insurers, the current fund level seems to be sufficient to cover the unexpected future loss of the non-life insurance industry because the accumulated fund exceeds 2.34 times the estimated fund level. In case III, $TVaR_{99.5\%}$ was 402.1 billion won and this was 28.28% of the deposit insurance fund for non-life insurers in 2019. Therefore, if the default probability by domestic rating agencies is used, the current fund level is 3.54 times higher than the average of worst loss with probability 0.5% within 3 years. In case IV, $TVaR_{99.5\%}$ was 2.434

trillion won and this amount was 171.17% of the deposit insurance fund for non-life insurers in 2019. This is also 147.52% of the lower limit of the target fund. That is, the current level of the deposit insurance fund is insufficient to cover the average of the worst case losses with a probability of 0.5% within 3 years. All these results are summarized in the following Table 13.

V. Conclusions

The deposit insurance system has achieved the results such as enhancing financial confidence, protecting consumers, resolution in insolvency of financial institution, and economies of scale for decades. However, there has also been criticism that the integrated deposit insurance fund system does not properly reflect the characteristics of each financial industry because it is only an integration of financial supervisory institutions. In particular, since the deposit insurance system has been operated mainly focusing on banks so far, it is needed to check the deposit insurance system such as the target deposit insurance fund and deposit insurance rate, reflecting the characteristics of non-banking sectors.

Globally, countries where insurers are protected by the single deposit insurer are very limited. In most countries, insurers are protected from insolvency by separate policyholder protection systems. In insurance sector, the severity of liquidity and systemic risk among the risks of insurers such as credit risk, liquidity risk and systemic risk, which are managed through deposit insurance, is significantly lower than that of banking entities. In addition, for the insurers, most of the various risks belonging to credit risks protected by the deposit insurers are managed through the strengthening of the regulatory system of Financial Supervisory Service. This implies that the insurers may be double-regulated. Meanwhile, interest risk is regulated by the RBC system as well. Insurers have prepared the various countermeasures for IFRS 17 or K-ICS plans, which are scheduled to be implemented in 2022. The regulation system for risk management has changed significantly since the deposit insurance system was introduced, and the fact that tightening regulations are scheduled in the near future should be considered in the application of deposit insurance standard to insurers.

In particular, in the case of non-life insurance business, the rate for the accumulation of fund in non-life insurance has fallen every year, making it difficult to reach the target fund level. In fact, if the non-life insurance industry is likely to fail, the deposit insurance premiums should be raised to increase the funding level. However, there is still a lack of acceptable evidence for non-life insurers.

Under these circumstances, this study attempts to present alternative ways to assess the appropriate target funds, focusing on non-life insurance industry. The existing studies use the Principal Component Analysis or scenario analysis to evaluate the adequacy of target fund. In addition, most existing studies use the KMV-Merton model to estimate the default probability. This study contributes to the evaluation of the target deposit insurance fund for non-life insurers by applying the credit migration method unlike the existing studies. We considered a $TVaR_{99.5\%}$ for the measurement of the expected worst loss with probability 0.5% in the loss distribution of deposit insurance fund by the credit migration method. The value of $TVaR_{99.5\%}$ in this study was between 67 billion won and 2.434 trillion won. This amount of money is from 4.71% to 171.71% of the current deposit insurance fund for non-life insurers, and from 4.06% to 147.52% of the target fund level for non-life insurers. However, if a rather extremely conservative case that reflects the loss of deposit insurance funds due to the bankruptcy of up to 7 insurers among non-life insurers that consists of the portfolio is excluded, the distribution of the $TVaR_{99.5\%}$ was between 67 billion won and 402 billion won. This money is from 4.71% to 28.28% of the current deposit insurance fund, and from 4.06% to 24.37% of the target fund level for non-life insurers. These results indicate that additional funding is unnecessary

because the current level of deposit insurance funds will sufficiently cover future losses. In addition, the findings point out that it is needed to review the adequacy of the current deposit insurance fund, given that unnecessarily excessive funding only lowers consumer welfare and efficiency by increasing insurance premium in non-life insurance.

However, there may exist a question as to whether the RBC system appropriately considers the various risks of the non-life insurance business. This is a limitation of this study, as it evaluates the deposit fund under the RBC system. Therefore, the risk of minimum guaranteed interest rate, catastrophe risk and liquidity risk are needed to be considered through further study. In particular, comparing the loss distribution for individual insurers under Solvency II and the RBC system is a future task of research.

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