ESTIMATING INDONESIA DEPOSIT INSURANCE'S EXPECTED LOSS USING ADJUSTED-CREDIT PORTFOLIO APPROACH

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BACKGROUND

Deposit insurance is one of the key elements of the financial safety net arrangement established to maintain public confidence in the national banking system. Referring to the banking system model of Diamond & Dybvig (1983), deposit insurance can avoid socially undesirable bank runs by providing guarantee to the depositor's funds in the banking system. To do so, a deposit insurer has to assure the public that it has an adequate amount of funds to absorb its potential losses caused by bank defaults. Thus, the size of the deposit insurance fund (DIF) becomes one of the main concerns of bank regulators and government.

In recent years, discussions about the proper methodology to determine the adequate amount of the DIF have been increasing. Most of the academic literatures related to the topic, such as Bennett (2001), Kuritzkes et al (2005), and Smirnov et al (2005), recommend the implementation of a risk management-based model for the assessment of the DIF. They argue that the loss distribution of deposit insurance is analogous to the credit loss distribution faced by a bank. Accordingly, a credit risk model that is commonly used by a bank to determine its loss reserve and economic capital level[2] could also be implemented in case of deposit insurance to determine its loss reserve and to evaluate DIF sufficiency. In IADI's survey research (2009a), this method, namely a credit portfolio approach, is found being implemented by several deposit insurers to determine or evaluate their reserve ratio, such as in Hong Kong, Singapore, United States, and Canada. In addition, this approach could also be used as a base for risk-based deposits assessment or pricing such as proposed by Ronn & Verma (1986), Dermine & Lajeri (2000), Laeven (2002), Maccario et al (2003), Sironi & Zazzara (2004), and Dev et al (2006).

In this paper, a credit portfolio model is applied to estimate the expected loss of Indonesia Deposit Insurance Corporation (IDIC) by using IDIC's internal rating of 121 commercial banks during January 2009-June 2011. Different from the former studies, the Cohort method is used to estimate the probability of default for each bank rating due to limited default data[3]. A fixed proportion of loss-given default (LGD) is assumed to all banks in the sample due to limited data of bank liquidation proceeds. Then, each bank's total deposits is used as the exposure-at-default (EAD), projected one year ahead using a classical decomposition technique considering trend, cyclical, seasonal, and random components. Finally, "the IDIC's annual expected loss" at the end of year 2011 is estimated under normal and stress scenarios.

LITERATURE REVIEW

It is reasonable to make the analogy between the risk faced by a bank on its loan portfolio and the risk faced by the deposit insurer on its bank portfolio. A bank will experience loss if a debtor fails to make scheduled payments regarding their loans from the bank, while a deposit insurer will suffer loss if there is a bank default. Thus, those kinds of losses faced by the bank and the deposit insurer can be classified as risks of counterparts

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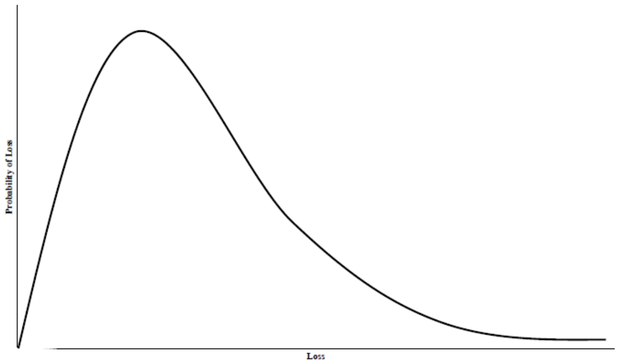
[2] See BIS (1999).
[3] The limited default data restricts us to use econometric model such as logistic regression, etc.

default. In addition, the loss distribution of a bank on its credit risk and a deposit insurer has similar form, i.e. long right skewed due to the positive probability of large losses caused by the failure of a large counterpart or the failure of a large number of counterparts.



Source: Bennett (2001), pp. 62.

Figure 1. The loss distribution faced by a bank or deposit insurer

However, there are a few important distinctions between the default of a loan and the failure of a bank. In case of a loan default, the bank will classify the loan as default when the debtor fails to make scheduled payments within the period stated by the loan agreement. While in case of a bank default, only the regulatory authority can revoke the bank's business license due to its insolvency below the capital level tolerated by the existing banking regulations. In addition, it is common that the government will provide a backup to the deposit insurer when it becomes insolvent. For this reason, some may argue that the potential risk to the DIF is irrelevant. Nevertheless, the backup funds will cost the taxpayers, thus instead of hurting the deposit insurer, this will cause a so-called "political pain" or political risk to the society (Kuritzkes et al, 2005). Thus, the insolvency risk of the deposit insurer is still relevant from the view of public finance.

The implementation of the credit risk model on deriving the loss distribution of a deposit insurer has been increasingly studied and discussed in recent years. However, the former studies with the same topic are still very limited including Bennett (2001), Kuritzkes et al (2005), Smirnov et al (2005), IADI (2009b)[4], and Saheruddin et al (2009). While similar studies applying a credit risk model to determine the risk-based premiums on the deposit insurance's member banks are Ronn & Verma (1986), Dermine & Lajeri (2000), Laeven (2002), Maccario et al (2003), Sironi & Zazzara (2004), and Dev et al (2006). Until this paper is written, this paper and the former one[5] are the first studies on implementation of a credit risk model to estimate the IDIC's expected loss.

The sample consists of of 121 commercial banks during the time period of January 2007-June 2009 sourced from the IDIC's bank database. It does not include rural banks due to very small market shares compared to the commercial banks. The commercial banks are divided into five groups according to their ownership, i.e. state-owned banks, private banks, local government banks, and foreign banks, and mixed ownership banks.

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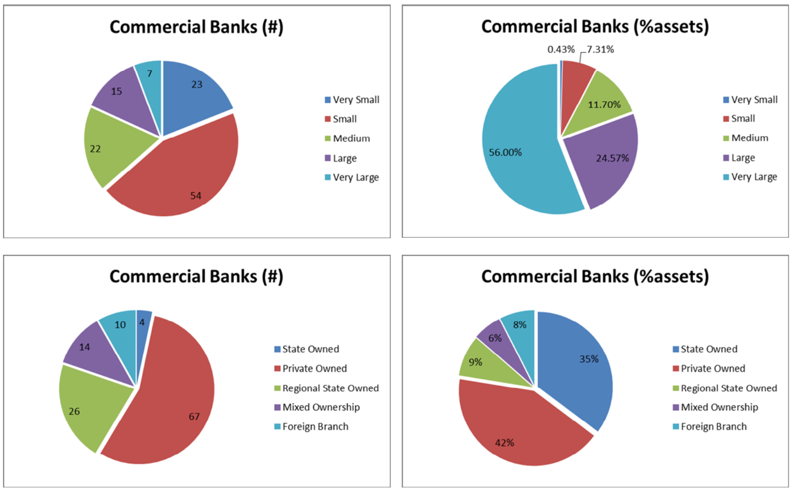
[4] After the surveys conducted by the International Association of Deposit Insurers (IADI) to its members during period 2008, IADI published a discussion paper with the title "Evaluation of Deposit Insurance Fund Sufficiency on the Basis of Risk Analysis" (April 2009b).

[5] Herman Saheruddin, Firdaus Djaelani, and Salusra Satria (2009), "Applying Credit Risk Model for Evaluating Deposit Insurance Fund Adequacy: The Case of Indonesia".



Source: IDIC, July 2009.

Figure 2. The composition of the member banks sample

Following the previous research, in this paper a one-year time horizon was chosen for the analysis. Thus, the expected loss would represent the suitable reserve for IDIC's losses for one-year ahead.

METHODOLOGY

The main output of a credit portfolio model is a loss distribution characterized by its expected and unexpected loss. The expected loss represents the amount of loss that the deposit insurer would expect to occur from the portfolio of member banks, while the unexpected loss measures the volatility of the deposit insurer's potential loss around expected loss over the chosen time period. In other words, the expected loss is equivalent to the mean of the loss distribution while the unexpected loss is equivalent to the standard deviation of the loss distribution. Thus, the deposit insurer's loss reserve is measured by the expected loss and the DIF sufficiency is evaluated by the unexpected loss.

Mathematically, in a credit portfolio model, the expected loss (EL_i) is the sum over the portfolio of the individual exposures-at-default (EAD_i) times the severity level or loss-given-default (LGD_i) times the probability of default (PD_i):

$$EL = \sum_{i=1}^{n} EAD_i \times LGD_i \times PD_i \tag{1}$$

In this paper, the individual EAD_i is measured by the projected total deposits of a member bank in the upcoming year. The LGD_i is assumed to be the same for the entire member banks, i.e. to value 100%, due to temporarily unavailable bank liquidation data. While the PD_i is estimated using Cohort method developed by JP Morgan in their CreditMetrics[6]. Instead of using bank external ratings from the independents rating agencies,

[6] Further see Gupton et al (1997), *CreditMetrics Technical Document*. JP Morgan.

the bank internal ratings provided by the IDIC's database is used to construct the probability transition matrix[7].

One of the critiques on using the Cohort method is that it ignores the state of the economy because it follows the Markov chain property (Jarrow et al, 1997). Thus, an adjustment to the credit portfolio model could be proposed by allowing stress test under different scenarios of economy conditions, i.e. normal and stress scenarios. To conduct the stress test, three explanatory variables are proposed, i.e. net-non performing loans, t-bond yield, and composite capital market indices. The change on the net-non performing loans represents the credit risk stress test, while the change on the t-bond yield represents the market risk stress test, and the change on the composite capital market indices is assumed to be the proxy of the stress test of other risks. As simplicity, a linear relationship between each member banks capital adequacy ratio (CAR_i) level with those explanatory variables is assumed as the equation below[8]:

$$CAR_i = \alpha + \gamma_1 NNPL_i + \gamma_2 YIELD + \gamma_3 INDEX \tag{2}$$

Further, the change on those variables would affect the overall financial condition of member banks; thus, shift the internal ratings of all member banks respectively. Then, both the IDIC's expected loss under normal and stress scenarios are estimated and finally the weighted average of the expected loss measures under those scenarios is calculated to determine the suitable IDIC's provision for insurance claims.

RESULTS AND DISCUSSION

IDIC evaluates its member banks condition every end of month based on the banks' monthly financial statements, thus the internal rating data are available periodically in a monthly basis[9]. Using the data, the monthly transition probability matrix is estimated using a discrete time rating migration approach (Cohort) as follow[10]:

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7 IDIC's member banks internal rating system classifies its member banks into 10 categories range from sound to unsound category based on assessment of Capital, Asset Quality, Earnings, and Liquidity aspects of member banks.

8 Though I propose those 3 explanatory variables, in this paper I only conduct the credit risk stress test because the rest of the equation still need further discussions.

9 IDIC's bank internal rating system is based on a point-in-time (PIT) philosophy instead of through-the-cycle (TTC), for further information of the optimal rating philosophies see Rikkers & Thibeault (2007).

10 The rows of the probability transition matrix show the initial rating at time-t, while the columns show the next period rating at time-t +1. For the details of a discrete time (cohort) vs continuous time (hazard) rating migration approach see Loffler & Posch (2007), pp. 46-57.

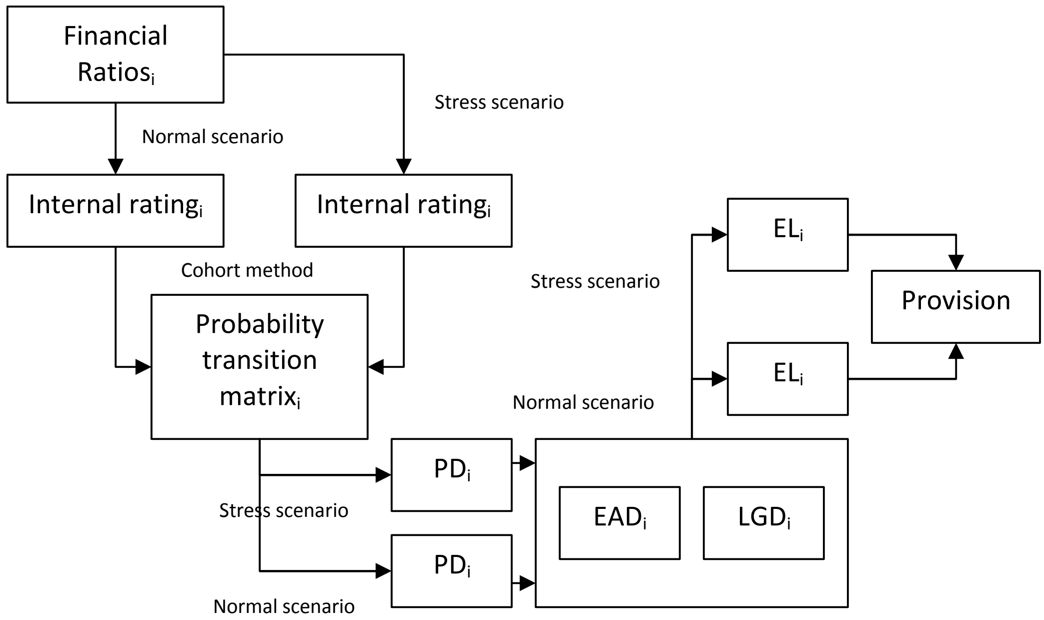

Figure 3. The IDIC's expected loss estimation stages

Table 1. Monthly transition probability matrix

	N	1	2	3	4	5	6	7	8	9	10	D	Σ
N	97.88%	0.00%	0.35%	1.06%	0.00%	0.00%	0.35%	0.00%	0.00%	0.35%	0.00%	0.00%	100.00%
1	3.45%	89.66%	6.90%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
2	0.00%	0.30%	83.73%	14.78%	0.75%	0.30%	0.15%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%
3	0.19%	0.13%	5.34%	83.79%	8.96%	1.34%	0.19%	0.06%	0.00%	0.00%	0.00%	0.00%	100.00%
4	0.19%	0.00%	0.38%	12.85%	78.61%	6.19%	1.50%	0.19%	0.09%	0.00%	0.00%	0.00%	100.00%
5	0.00%	0.00%	0.72%	3.58%	18.85%	67.78%	6.44%	1.91%	0.72%	0.00%	0.00%	0.00%	100.00%
6	0.36%	0.00%	0.36%	1.44%	2.53%	14.80%	74.73%	5.05%	0.36%	0.36%	0.00%	0.00%	100.00%
7	0.00%	0.00%	0.00%	2.56%	0.85%	4.27%	16.24%	69.23%	6.84%	0.00%	0.00%	0.00%	100.00%
8	0.00%	0.00%	0.00%	0.00%	2.50%	7.50%	7.50%	10.00%	65.00%	7.50%	0.00%	0.00%	100.00%
9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	2.50%	7.50%	2.50%	85.00%	0.00%	2.50%	100.00%
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	100.00%
D	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	100.00%

The rows of the probability transition matrix in Table 1 above show the initial bank rating at month t, while the columns show the next period bank rating at month t+1. The transition probability value along the main diagonal indicates the probability of a bank with certain rating stays in the same rating at the following month.

The non-rated (N) rating refers to the unrated category, which represents events such as a new bank entrant or a bank merger. In this paper, the N rating transition probabilities are not adjusted further due to their lack of meaningful economic interpretation[11]. However, this is still acceptable as long as the N category is assumed as an absorbing state as well as the default (D) rating.

Then, the monthly transition probability matrix is converted into an annual transition probability matrix using the multi-period transition adjustment method proposed by Loffler & Posch (2007), as shown below.

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[11] However, there are some methods can be used to eliminate the N category from the transition probability matrix, further see Loffler & Posch (2007), pp. 51-52.

Table 2. Annual transition probability matrix

	N	1	2	3	4	5	6	7	8	9	10	D	Σ
N	77.50%	0.09%	3.40%	8.38%	3.52%	1.67%	2.14%	0.83%	0.29%	1.83%	0.00%	0.3499%	100.00%
1	21.42%	27.47%	21.49%	19.32%	6.59%	1.90%	1.05%	0.30%	0.09%	0.35%	0.00%	0.0378%	100.00%
2	1.29%	1.24%	23.98%	42.31%	20.77%	6.26%	2.89%	0.87%	0.29%	0.10%	0.00%	0.0073%	100.00%
3	1.84%	0.76%	15.58%	41.14%	25.79%	8.50%	4.32%	1.38%	0.47%	0.20%	0.00%	0.0169%	100.00%
4	1.78%	0.42%	10.87%	36.37%	29.32%	11.18%	6.58%	2.26%	0.80%	0.39%	0.00%	0.0438%	100.00%
5	1.39%	0.30%	8.70%	31.32%	29.01%	13.62%	9.68%	3.68%	1.35%	0.82%	0.00%	0.1254%	100.00%
6	2.07%	0.20%	6.42%	24.66%	26.25%	16.22%	14.45%	5.82%	2.10%	1.51%	0.00%	0.3058%	100.00%
7	1.32%	0.17%	5.41%	21.40%	23.49%	16.68%	16.79%	8.04%	3.25%	2.86%	0.00%	0.5981%	100.00%
8	1.04%	0.13%	4.47%	18.77%	21.44%	15.46%	16.05%	8.89%	3.93%	6.90%	0.00%	2.9215%	100.00%
9	0.60%	0.05%	2.07%	9.58%	12.03%	11.82%	15.78%	11.63%	4.88%	16.88%	0.00%	14.6909%	100.00%
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.0000%	100.00%
D	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	100.0000%	100.00%

The column D of the Table 2 above shows the probability of transition of each rating to the default category. Instead of using the probability of the column D as the PD of each member banks, the PD is defined as the probability of transition of a member bank from its current rating to "problematic-bank" rating, i.e. 9, 10, or D. Thus, the PD of each member bank rating is sum between column 9, 10, and D.

Assuming a fixed LGD of 100% and annual deposit growth rate of 8.92% from the classical decomposition technique, the IDIC's expected loss at the end of year 2009 would equal an IDR 10,149,699 millions under normal scenario. Then, to conduct a credit risk stress test, the parameters of the equation (2) are estimated as below:

$$CAR_i = 30.96757 - 2.493288 NNPL_i \qquad (3)$$

By assuming the average banking industry net-non performing loans during the upcoming year change would increase as much as 1.06%[12], the IDIC's expected loss at the end of year 2009 would equal IDR 16,586,615 millions under stress scenario. Finally, the IDIC's provision for insurance losses is the weighted average of both expected loss measures under normal and both scenarios with 60% to 40% weight[13] of normal and stress scenarios, i.e. as much as IDR 13,360,689 millions. This is the amount of loss reserves that are probable and estimable and could be proposed to be used in IDIC's balance sheet on the liability side.

CONCLUDING REMARKS

The similarity of characteristic between the credit risk faced by a bank and claim risk faced by a deposit insurer are both caused by counterparts default and permits the application of the credit risk model in deriving the deposit insurer's loss distribution. This paper aims to propose an adjusted-credit portfolio model to estimate the IDIC's expected loss that capable of accommodating a stress test. The main components of the expected loss model are EAD, LGD, and PD. The member banks' EAD are projected total deposits using a classical decomposition method, the LGD is assumed to be 100% due to temporarily unavailable bank resolutions data, while the PD of each rating category of member banks is estimated using the Cohort method adjusted from JP Morgan's CreditMetrics. Different from the previous researches, the basic model is adjusted to allow changes for stress testing purposes.

Using the adjusted-credit portfolio model, the IDIC's expected loss at the end of 2011 would equal an IDR 10,149,699 millions under normal scenario and IDR 16,586,615 millions

[12] This number is assumed as 2 × average banking industry net-non performing loans during the sample period.

[13] These weight are based on my conservative-subjective judgment, comments are welcome.

under stress scenario. Finally, the IDIC's provision for insurance losses is the weighted average of both expected loss measures under normal and both scenarios with 60% to 40% weight of normal and stress scenarios, i.e. as much as IDR 13,360,689 millions.

Since this research is still on its initial stage of development, some assumptions might be over-simplified. However, this paper might be a trigger for the next researchers to learn this field more thoroughly and develop more accurate deposit insurer's loss distribution models.

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