Adequacy of Existing Level of Capital Implied by the Basel Standards Relative to the Credit Risk Exposures of Banks in the SEACEN Region

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FOREWORD

This research project "Adequacy of Existing Levels of Capital Implied by the Basel Standards Relative to the Credit Risk Exposures of Banks in the SEACEN Region" is an outcome of another collaborative effort between the SEACEN Centre and selected member central banks of Indonesia, the Philippines, Sri Lanka, Thailand and Nepal. This project is part of the SEACEN research activities for Operating Year 2005/06 which was approved at the 3rd SEACEN Executive Committee Meeting in Colombo, Sri Lanka on 29 January 2005. It aims to measure the level of risks in the banking system using available supervisory information, and compare it with the level of capital as implied by Basel Standards. The study would enable bank supervisors to determine whether the existing level of capital in their respective banking systems is commensurate to the level of risks implied by supervisory information.

The paper is divided into two major sections. The first section provides a consolidation of the results of the individual country studies prepared by the Project Leader, Mr. Nestor Espenilla Jr., Deputy Governor of the Bangko Sentral ng Pilipinas, while the second part presents the respective country papers.

The author wishes to thank the individual country researchers from participating SEACEN member central banks who contributed to this project: Ms Mirza Yuniar I. Mara and Ms Khairani Syafitri, Junior Banking Researchers of Bank Indonesia, Ms Marissa L. Barcenas, Bank Officer III of Bangko Sentral ng Pilipinas, Mr. V. Sivanesan, Assitant Director, Central Bank of Sri Lanka, Mr. Sachin Jung Rayamahji, Assistant Director, Nepal Rastra Bank and Mr. Don Nakornthab, Senior Economist and Dr. Amporn Sangmanee, Senior Executive, Bank of Thailand. At the SEACEN Centre, the author wishes to put on record his appreciation to Dr. Bambang S. Wahyudi and Ms Chew Hong Yng for facilitating technical consultations between the researchers and the author in two workshops held in Malaysia.

The views, conclusions and recommendations stated in the paper are those of the authors and do not necessarily reflect those of the SEACEN Centre or its member central banks.

Dr. Subarjo Joyosumarto
Executive Director
The SEACEN Centre

30 June 2006

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EXECUTIVE SUMMARY

This collaborative research project aims to measure the level of risks in the banking system using available supervisory information with the view to determine whether the existing levels of capital is commensurate to the level of risks implied by them. This supervisory information includes data on loan accounts that are either past due or current as classified by the supervisors and the provision set aside for these loans.

The study finds that simulating the credit loss distribution using the data on loan loss provision and estimating the Value-at-Risk (VaR) as the upper limit of the distribution would result to measures of capital (derived as the residual of the VaR value and the sum of provision for past due accounts) that underestimates the capital as implied by either the Capital Adequacy Ratio (CAR) or by the risk-based capital for loan portfolio alone. On the other hand, simulating the distribution of credit losses using the actual loss given default rate on defaulted accounts and estimating VaR and consequently, the capital for unexpected losses from this distribution would result to capital larger than that implied by the risk-based capital for loan portfolio alone. The same trend is observed when comparison is made between VaR and the sum of capital implied by CAR and the specific provision.

The study made use of bootstrapping technique in simulating the credit loss distribution with the STATA software facilitating the process. The lack of historical data for most SEACEN countries delimited the study to using stock data in its estimation.

The study recommends that for robust estimation of capital, the procedure must be used for data that reflects or takes account of the economic cycle. It also recommends that a more complete data be gathered to facilitate comparison with model-based methodologies for credit risk measurement and to take account of the risk accounted for by risk assets other than the loan portfolio of the bank.

CHAPTER 1

ADEQUACY OF EXISTING LEVEL OF CAPITAL IMPLIED BY THE BASEL STANDARDS RELATIVE TO THE CREDIT RISK EXPOSURES OF BANKS IN THE SEACEN REGION

by
Nestor Espenilla Jr.[1]

1. Introduction

The issuance of the revised framework for capital measurement by the Basel Committee on Banking Supervision (BCBS) in June 2004 poses great challenge among SEACEN countries. This revised framework of the International Convergence for Capital Measurement and Capital Standards or more commonly known as Basel II, aims to make the existing risk-based capital measurement more risk sensitive. However, in the process of formulating the entire framework, the BCBS used information and resources that are reflective of the more advanced markets and not of emerging markets like most SEACEN countries are. Despite the seeming complexities of the new framework, most banking supervisory bodies in the SEACEN region have signified their intention to adopt the new framework.

As it was based on more advanced market, the region will necessarily encounter difficulties in adopting the new framework. For credit risk in particular, the new framework introduced two (2) basic approaches by which banks may compute their capital requirements that are deemed more reflective of the level of risk in their portfolios. The first approach, the standardized approach, requires the use of external credit rating agencies' assessments in order to determine the required capital for assumed portfolios. However, majority of bank in the region are unrated and lacking in market-quoted claims. The second approach, the internal ratings based approach, determines default probabilities through the use of internal ratings and uses a complex credit risk algorithm which is a function of the default probabilities and other parameters to estimate capital measurements. However, the possible mismatch in the level of sophistication and resources available in the G10 counterparts that serve as basis for the algorithms used with that of the region poses great difficulties in adopting these approaches. In particular, many SEACEN countries lack credit bureaus and if there is any the information contained therein is very limited. As such, whatever detailed and

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richer information available at the bank may not be available to supervisors. In fact for most of the supervisors, the only data available are bank level data found in financial statements.

Due to these limitations, the intention is to adopt these approaches on a gradual basis among SEACEN countries. On the interim however, how can supervisors assess the adequacy of existing levels of capital implied by the Basel Standards relative to the credit risk exposures of banks in the SEACEN region? This research project tried to explore ways of measuring credit risk by using current available information. It explored the use of re-sampling technique in measuring the credit loss distribution using either the data on provision for Non-Performing Loans/Advances (NPL/NPA) or a measure of Loss Given Default (LGD) Rate based on actual sale of NPL/NPA in the respective countries. From the estimated distribution, the Value-at-Risk (VaR) was estimated and a measure of unexpected loss was derived by subtracting the expected loss from the VaR value.

This research project was intended to be participated in by 10 countries (Malaysia, Mongolia, Brunei, Taiwan, Korea, the Philippines, Indonesia, Thailand, Nepal and Sri Lanka). However, due to data limitations, only five countries were able to complete their research on schedule. These are Indonesia, Philippines, Sri-Lanka, Thailand and Nepal.

2. Data and Data Limitations

The country researchers made use of either the data on all/part of the entire loan portfolio or only those loans that are classified for selected commercial banks chosen on the basis of their contribution to the total assets of all commercial banks in their respective countries or on the basis of availability of data to perform the simulation process. While it is recognized that assets other than loan portfolio of banks contribute to total credit risk faced by banks, the lack of required details and the complexity of the risks on other assets delimit the study to using only loan accounts. In addition, for most of the SEACEN countries, there exist no definite guidelines in classifying other risk assets which may contribute to unquantifiable errors in estimation.

3. NPL/NPA or Default Criteria and the Setting Up of Provision

For most of the country papers included in this report, credit risk was estimated using the data on NPL/NPA. NPLs/NPAs are determined basically on the basis of loan quality and ageing criteria which for four out of five participating countries the number of days past due conforms to the Basel II definition of default which is ninety (90) days past due. The only country that classifies loans past due for at least thirty days as NPL is the Philippines. However, the other criteria for a default occurrence as defined in Basel II are met by the NPL definition in the Philippines.

Below are the country specific criteria for defining default or classifying non-performing loans and the setting up of provision for these accounts:

3.1 Indonesia

Central Bank of Indonesia (BI) set factors in classification of credit quality based on prospects, debtor performance and repayment capability. Credit quality is classified as Current, Special Mention, Sub-Standard, Doubtful or Loss. Non-earning assets are assets of the bank other than earning asset with potential for loss including but not limited to foreclosed collateral, abandoned property, interoffice accounts and suspense accounts, including loans categorized as Sub-Standard, Doubtful or Loss. A loan is non-performing subject to the following criteria:

a. Prospects: Business shows very limited growth or even declining. Relations with affiliated or group companies beginning to generate impacts that burden debtors. Inadequate environmental management actions failing to meet minimum requirements stipulated in applicable laws and regulations, material breach to existing regulation.

b. Debtor performance: Business have very low earning or even suffer from loss, moderate to high debt-to-equity ratio, liquidity difficulties and business activity susceptible to changes in exchange rate and interest rates.

c. Repayment Capacity: There is outstanding debt or arrears in principal and/or interest exceeding 90 days. Repeated overdrafts incur mainly to cover operating losses and cash flow shortage. There is moderate to serious breach of key terms and conditions or covenant of credit.

BI does not allow accrual of interest income for loans classified as non-performing (foreclosed collateral) until the income is realized. Provision for these accounts depend on the number of days past due and security arrangements, if any and are determined as follows, after deducting collateral: (1)15 percent for sub-standard; (2) 50 percent for doubtful; and, 100 percent for loss.

3.2 Philippines

The Bangko Sentral ng Pilipinas defines Non-Performing Loans (NPL) as loans that are (a) unpaid for thirty (30) days or more after due date or after they have become past due (for loans payable in lump sum, or in quarterly, semi-annual or annual installments); (b) have three (3) or more installments in arrears (for loans payable in monthly installments); and; (c) are restructured (subject to certain criteria).

BSP does not allow accrual of interest income for loans classified as non-performing. Provision for these accounts is determined as follows: (1) five percent for specially mention; (2) 10 percent for substandard secured; 25 percent for substandard unsecured; 50 percent for doubtful; and 100 percent for loss loans.

Although the above definition of NPL in terms of the number of days past due is not strictly aligned with Basel II definition of default, some other criteria mentioned in the Basel document conforms with the BSPs criteria for NPL such as when the bank puts the credit obligation on non-accrued status and when the bank makes a charge-off or account-specific provision resulting from a significant perceived decline in credit quality subsequent to the bank taking on the exposure.

3.3 Sri Lanka

The Central Bank of Sri Lanka (CBSL), the supervisory authority in Sri Lanka, defines Non-Performing Loans (NPL) as the capital and/or interest of advances that are in arrears for a period of three months or more. This is consistent with the Basel II definition of default. Overdraft accounts exceeding the approved limit for three months or more are also considered as NPL. Depending on days past due, these accounts were classified as substandard, doubtful or loss with provision for possible loss determined as follows (net of realizable security value and interest suspense): (1) 20 percent for substandard; 50 percent for doubtful; and 100 percent for loss accounts.

3.4 Thailand

Bank of Thailand classifies loans as default depending on the combination of ageing and quality criteria. These are loans classified as substandard, doubtful and loss. Substandard loans have interest overdue more than 3 months, but not more than 6 months. Doubtful loans have interest overdue more than 6 months, but not more than 12 months. Loss loans have interest overdue more than 12 months. Beyond the aging criteria, there are quality criteria that look at projected cash flows and the ability of the debtor to repay the debt in entirety.

Minimum loan loss reserves for these accounts are determined as follows (1) 20 percent for substandard; (2) 50 percent for doubtful; and 100 percent for loss loans. Provisions are calculated net of deductible collateral. If the amount of deductible collateral is more than the amount of outstanding loan balance, then no provision is needed.

For more details on the guidelines and definition of each of the classification used by respective countries, please refer to the respective country reports.

3.5 Nepal

Nepal Rastra Bank (NRB), the regulatory body of all deposit taking institutions in Nepal defines default on an ageing (past due) basis. These loans are those loans classified as substandard, doubtful and loss and are also considered as non-performing loans. Substandard loans are those that are three to six months past due. Doubtful loans are those that are past due from 6 months to one year while loss loans are those that are past due for more than one year. Loans that meet the following criteria are also classified as loss loan irrespective of their past due or expiry dates: (1) If the loan is unsecured; If the borrower is declared insolvent; If the borrower has disappeared or is absconding; (2) If the bills purchased or negotiated remains unsettled within 90 days. Similarly, if the force loans created out of Letter of Credit obligation or invocation of guarantees are not settled within 90 days, they are also to be classified as Loss Loans.; (3) If the auction for recovery has been in process for more than 6 months or the case for recovery is under litigation; (4) If the loan is extended to borrowers that are blacklisted by the Credit Information Center of Nepal; (5) If the project/business cannot commence its operation or if the project/business is not in operation; and (6) If the credit card dues have not written off within 90 days

Loans classified as substandard are subject to 25 percent provision, doubtful with 50 percent provision and loss loans with 100 percent provision.

4. The Methodology Used

This project explored the use of bootstrap in the generation of the credit loss distribution from which the VaR was estimated. Bootstrap is a re-sampling technique developed by Bradley Efron et.al (1979). It is a computer intensive method in deriving standard errors of estimates from information in the sample. It is a type of Monte Carlo method applied based on observed data. The technical description of bootstrap is provided either as Annex as in the Philippines report or as part of the main report in the other countries.

Specifically, the proposed procedure is described below:

(1) Using the data on provision (Approach 1): from the pool of classified accounts, a random sample of size n (n is the total number of classified accounts of the bank in consideration) was taken (Step 1). From this sample, the total amount of provision was computed (Step 2). These two steps were repeated r times. Since the concern was the estimation of the tail of the distribution, it was necessary to produce a large number of replicates such that r was set at 20,000 or 25,000 (1,000 for Indonesia).

(2) Using LGD estimate (Approach 2): Using a measure of LGD, expected loss of the loan portfolio was estimated as the product of LGD rate and the outstanding balance of defaulting loans. Note that the probability of default for defaulted accounts is one (1), hence expected losses is measured as the product of LGD rate and outstanding balance. In the case of the Philippines, the resulting data set of expected losses was taken as the initial sample from which re-sampling was done to generate the distribution of credit losses. That is, a sample of size n was taken r times with the sum of expected losses computed for every replicate.

For Sri Lanka, a representative sample of loan accounts containing both performing and non-performing loans was taken as initial sample. From each of the accounts, the proportion of losses was taken. Effectively, simulation is done on the estimated proportions.

To facilitate the process of re-sampling, the country researchers used either E-Views or STATA with some computations aided by SAS and Excel.

From each of the simulated distribution, parameters such as the mean loss and variances were estimated and the maximum amount of losses that can be experienced from bank's classified accounts at five (5) percent, one (1) percent and 0.1 percent confidence level over the assumed time horizon was computed using the Value-at-Risk (VaR) concept. Since VaR is composed of both the expected (EL) and unexpected losses (UL), the capital level, K_{cl}, that would be sufficient to cover banks' unexpected loss for classified accounts was derived by subtracting the expected loss from the VaR value.

5.1 Result

In general, Approach 1 is based on the assumption that provision is a good measure of EL as implied by its current use in the banking system (ie. provision for expected losses). This approach was used by four countries namely, Thailand, Philippines, Nepal and Indonesia albeit with some slight modification for its first simulation by Thailand. Instead of using classified accounts alone, Thailand made use of all "large" loans in its first simulation process including those that are classified as current and measures the provision associated to the simulated portfolio. The simulated capital was then expressed as a percentage to total loan portfolio and compared either to the overall capital as measured by Capital Adequacy Ratio (CAR) (Indonesia, Thailand, and Nepal) or to the risk-based capital that can be derived from NPLs/NPAs alone (Philippines). Results for these four countries showed that the estimated UL underestimates the regulatory capital as measured either by CAR or by the capital for NPLs/NPAs only. The proportion of capital however follows the direction of the percentage of NPLs in the loan portfolio. The underestimation is partly attributed to the fact that the simulation was done using loan accounts only while CAR measures capital for all assets of the bank. In the Philippines case, underestimation can be attributed to the fact that the regulatory capital was computed for the entire loan portfolio while the simulation measures losses that are due from classified accounts only.

Since simulation was done on classified accounts only, the estimated UL was also expressed as a percentage to total NPLs/NPAs in the paper by Indonesia, Philippines and Thailand. Except for the Philippines, the percentage derived was compared with the overall CAR. The Philippines however derived the regulatory capital that should be obtained for the NPLs since the expected losses used in the simulation measures expected losses from NPLs alone. In both approaches, the general results showed proportions of simulated capital larger than the regulatory capital. This result was deemed supportive of the move by the Bangko Sentral ng Pilipinas (BSP) to increase risk weight for NPLs from 75 to 100 and 125 to 150, for NPL (Housing) and NPL (All Other Assets), respectively, in 2007.

Approach 2 was used by Sri Lanka and Philippines however with differing LGD rate and sample data used. Sri Lanka used an LGD of 50 percent and only a representative sample of the entire loan portfolio of the bank while Philippines used an LGD rate of 73 percent using only defaulting accounts. Both countries used only defaulted accounts (hence, the probability of default is equal to one) which in effect means simulating on actual loan portfolio losses however using stock data for the specified reporting period.

The resulting UL was again expressed as a proportion of total loan portfolio. The Philippines compared the estimated UL with the risk-based capital for the total loan portfolio alone and not with CAR value in recognition of the fact that the contribution of other assets other than the loan portfolio to total credit risk are not accounted for in the simulation due to data limitations. Sri Lanka compared the total of regulatory capital plus provision with the overall VaR value.

For the Philippines, results showed that the estimated UL exceeds the regulatory capital which is 10 percent of risk-weighted loan accounts. In the case of Sri Lanka, the resulting UL underestimates the required capital as expressed by the CAR. However, summing up the provision and the risk-based capital for the loan portfolio and comparing the sum with the VaR value showed the opposite. In this case, Sri Lanka have inclined that a more appropriate comparison should be between VaR and the total of provision and capital in order to assess the capital adequacy of banks.

6. Conclusion and Recommendations

The simulation of credit loss distribution using the data on classified accounts is based on the assumption that provisions cover expected losses. Results show that using this data in simulating the credit loss distribution would yield estimates lower than the overall regulatory capital as measured by overall CAR, except for cases when the classified accounts represent a large portion of the total loan portfolio.

Limiting the comparison between the proportion of unexpected losses to total classified accounts and the capital derived by risk-weighting NPLs only showed the opposite picture. The estimated capital proved to be larger than the regulatory capital. This suggests that the use of a higher risk weight for classified accounts is appropriate as deemed by the Bangko Sentral ng Pilipinas. Results in the Philippines using Approach 2 further support this case in which the resulting percentages of unexpected losses are greater than the risk-based capital.

Robust estimation for capital however, requires data spanning at least one whole economic cycle and the use of the methodology for all types of banks. Thus, before making any policy recommendation there is a need to use the methodology for more banks and for several years of data to establish the trend.

Furthermore, there is also a need to gather a more complete data (covering not only the classified accounts but all accounts and data on annual losses) to facilitate comparison of the estimates using model-based methodologies as suggested by the more advanced approaches in measuring credit risk. It should also be recognized that in addition to other sources of credit risk unaccounted for in the simulation, other forms of risks such as market risk, liquidity risk and concentration risks should be taken into consideration in reserving capital.

If the trend is established by historical data, an alternative to increasing risk weight is to increase provision rates for classified accounts.

CHAPTER 2

ADEQUACY OF THE EXISTING LEVELS OF CAPITAL IMPLIED BY THE BASEL STANDARDS, RELATIVE THE CREDIT EXPOSURES OF BANKS IN INDONESIA

by

Mirza Yuniar Isnaeni Mara and Khairani Syafitri[2]

1. Introduction

The Basel Committee on Banking Supervision (BCBS) has issued last 26 June 2004 the revised framework for *International Convergence of Capital Measurement and Capital Standards*, or more popularly known as Basel II. Most, if not all, banking supervisory bodies in the SEACEN region have signified their intention to adopt Basel II. Indonesia has set implementation of Standardized Approach in credit risk calculation in 2008 with the Internal Ratings Based (IRB) approach in 2010.

The region, however, may encounter difficulties in implementing any of the two approaches described in the framework. For one, the limited number of rated claims in the SEACEN region will effectively render the standardized approach less effective. Currently, Indonesia has two rating agencies and only few bank exposures that are rated. In particular, only around 104 companies have corporate ratings for bond issuances. In addition, the country is facing difficulty to get market price for marking to market of collateral and asset value due to lack of liquidity in Indonesian capital market which is reflected in low market capitalization vis-à-vis GDP equal to 29.4 percent as of December 2005. Consequently, all unrated assets will have to be risk weighted at 100 percent meaning the capital level will not differ from the current capital level based on Basel I. At the moment, BI has introduced lower regulatory capital for claims considered as low risk exposure based on Basel II, such as retail portfolio and residential mortgage.

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2. Junior Banking Researchers, Bank Indonesia. Special thanks is also extended to Mr. Muliaman D. Hadad and Mrs. Murniastuti – the Director and Deputy Director of Banking Research and Regulation Directorate. Special tribute also due to many people who has helped in completion of the draft which among others are Mrs. Trisnawati Gani, Mr. Wimboh Santoso and Mr. Imansyah from Directorate of Banking Research and Regulation. We would like to thank also Mr. Deddy Ariyadi and Mr. Wahyu Hidayat from Directorate of Banking License and Information for providing beneficial data and information.

The IRB approaches, on the other hand, appear too complex for both banks and banking supervisors in the region to immediately implement in view of their data requirements. Note that the complex credit risk algorithm prescribed under these approaches was calibrated using data from developed countries. These data are not necessarily available in the developing countries in the region. Moreover, there is unequal access between banks and supervisors to any information available since many of the countries in the region have no credit bureau or their credit bureaus have rather limited information. As such, the detailed and richer information available at the bank may not be available to supervisors.

In the case of Indonesia, Central Bank of Indonesia (BI) has already built a debtor information system or credit bureau which requires bank to report any loans with notional amount of at least Rp50 million (equivalent to USD5,000). Moreover, it is also developing credit bureau establishment which currently is at its initial stage. This credit bureau will be able to provide borrower level data such as amount of loan from Rp1,00 and type of collateral, guarantee and facility and debtor's monthly financial statement. Debtor's data available include not only banks' debtors but also debtors' of other financial institution, public service companies (phone, electricity and gas). This borrower's data is envisioned to be accessed real-time on-line.

While the information required for the more advanced approaches are still unavailable, is it possible then for the supervisors to asses the adequacy of the existing levels of capital implied by the Basel Standards, relative to the credit risk exposures of banks in the SEACEN Region using current available information?

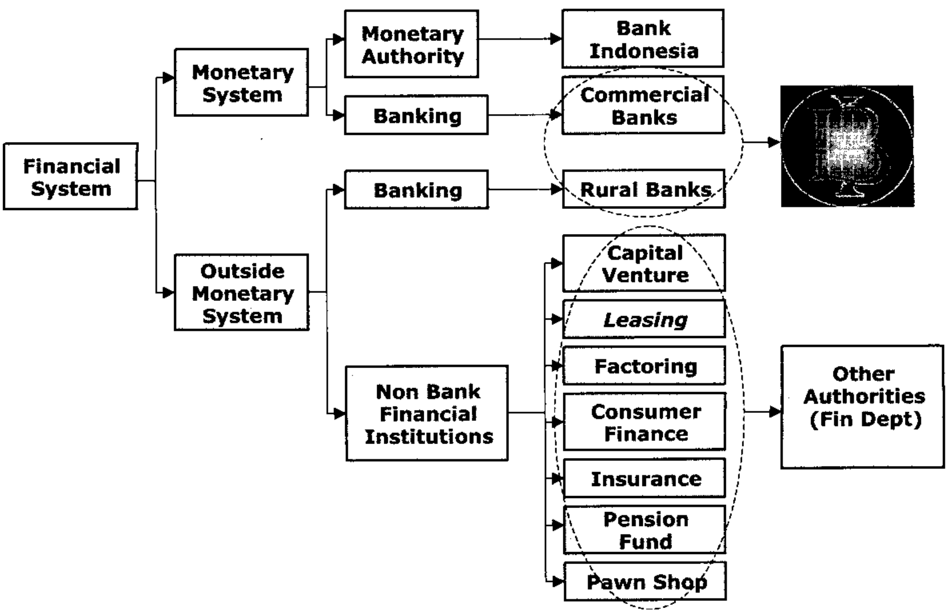
This study tried to explore ways of measuring credit risk using the Value-at-Risk approach and bootstrap procedure to come up with a measure of credit risk faced by banks using information on classified loan accounts of some banks retrieved from BIs current credit bureau data. Other elements of credit risk are not considered in this study. The credit risk estimated from this model is an expected loss (EL) figure, which can be used to derive a level of capital adequate to cover a specified level of risk, using the value-at-risk approach.

The paper proceeds as follows. Section 2 presents preface of Indonesian banking system. Section 3 elaborates methodologies commonly used to measure credit risk. Section 4 covers default definition based on BI's regulation, Section 5 will presents the results and compares values of bank capital associated with predefined insolvency levels with the regulatory capital required under the proposed method. Section 6 concludes.

2. Indonesian Banking System

Similar to other financial system in most countries, the Indonesian financial system basically constitutes financial market network and institutions, business sectors, households, and central banks and government institutions. Such financial system has functions starting from arranging the payment mechanism, providing funds/loans, creating money to serving as medium of savings. Basically, the system functions as the intermediary between the investors who own money to invest and the borrowers who need money to spend. Figure 2.1 depicts the Indonesian financial system.

Figure 2.1
Indonesian Financial System



As stipulated in the Banking Act No. 7 of 1992 as amended with the Act No. 10 of 1998, there are 2 types of banks in Indonesian banking system. The first is recognized as General or Commercial Bank and the second known as Rural Bank. The basic distinction between those types is the capability of issuing demand deposits to their depositors that can only be provided by the first. Also, the General or Commercial Bank may render its services on an extensive basis and may operate within the country or overseas. On the contrary, based on its characteristics, several restrictions have been placed upon the operational scope of the Rural Bank, as to the limited operating territories and limited type of services. Commercial banks comprise of 6 groups of banks as depicted in the Table 2.1. This study focuses only on commercial bank.

Since around 90 percent of funds in our financial system is handled by the banks, up to now banking still has very pivotal position in our economy. Total number of general banks in Indonesia is 131 banks with 8,236 offices, far below total number before the crisis (238 banks). The greater contribution of credit risk comes from loan portfolio since it dominates the asset portfolio.

Key indicators of Indonesian commercial banks are given in Table 2.2. below. As provided in Figure 2.2. NPLs level shows significant decline from crisis period on year 1997-1998. However from December 2004, the NPLs gross and NPLs net of provision start to crept upward sluggishly. The NPLs account for the largest portion of classified account hence the trend also applies to the trend of classified accounts.

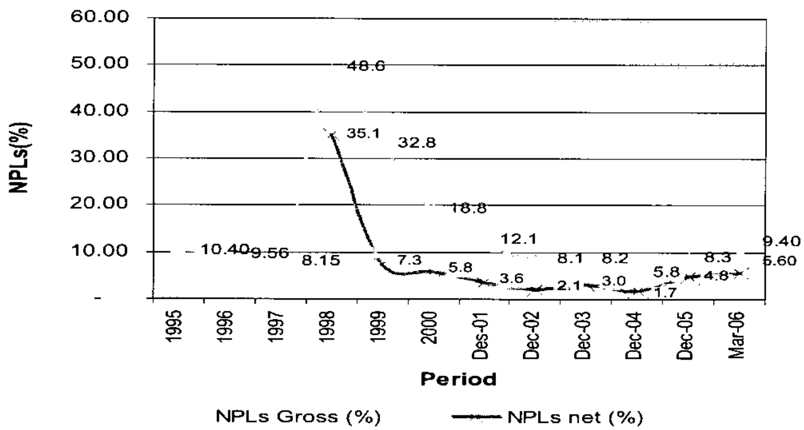
Table 2.1
Number of Banks and Bank Offices

Category of Bank	Position			
	2002	**2003**	**2004**	**2005**
Commercial Banks				
Number of Banks	141	138	133	131
Number of Offices	7,001	7,730	7,939	8,236
State Banks				
Number of Banks	5	5	5	5
Number of Offices	1,885	2,072	2,112	2,171
Regional Development Banks				
Number of Banks	26	26	26	26
Number of Offices	909	1,003	1,064	1,107
Private Foreign Exchange Banks				
Number of Banks	36	36	34	34
Number of Offices	3,565	3,829	3,947	4,113
Private Non-Foreign Exchange Banks				
Number of Banks	40	40	38	37
Number of Offices	528	700	688	709
Joint Venture Banks				
Number of Banks	24	20	19	19
Number of Offices	53	57	59	64
Foreign Banks				
Number of Banks	10	11	11	11
Number of Offices	61	69	69	72

Table 2.2
Commercial Banks' Key Indicators

Indicators	**Dec-04**	**Dec-05**	**Mar-06**
Total Assets (Rp Tr)	1,272.3	1469.8	1465.3
Deposit Funds (Rp Tr)	963.1	1127.9	1123.9
Credits (Rp Tr)	595.1	730.2	722.7
LDR (percent)	61.8	64.7	64.3
NPLs Gross (percent)	5.8	8.3	9.4
NPLs net (percent)	1.7	4.8	5.6
CAR (percent)	19.4	19.5	21.7
NIM (NII/AP) (percent)	0.6	0.5	0.5

Figure 2.2. Indonesian Banks' NPLs 1995-2006



3. Methodology and Data

3.1 The Proposed Approach

The most commonly used methodologies to estimate credit loss distribution of a loan portfolio are model-based approaches. Simplifying assumptions are employed in model development to represent reality and may impose unwarranted restrictions on reality which lead to model risk, or may rest the model on unobservable parameters that can be approximated only with errors incurring measurement error.

This study uses bootstrapping technique to minimize the impact of such errors on the estimation of the credit losses distribution function and to mimic the shape of the loss distribution function of any specific loan portfolio at a specific period of time. This technique also enables replication of the real risk faced by banks without specific knowledge or assumptions regarding risk or correlation among different risk factors inherent in the actual credit loss distribution.

Bootstrap is a computer-intensive method developed by Bradley Efron (1979) and others to derive standard errors of estimates from information in the sample and do statistical inference. Bootstrap is a non-parametric procedure, hence we can do the simulation even without checking the normality of the distribution of the underlying population.

Capital allocation system generally assumes that it is the role of reserving policies to cover expected credit losses, while it is that of economic capital to cover unexpected credit losses.

As mentioned, expected loss can be viewed as the summation of all provisions made at different credit classification categories. In most credit risk models expected loss for a certain credit facility is estimated as the product of expected default frequency (EDF), loan equivalent exposure (LEE) and expected loss rate given default (LGD), i.e. EL = EDF*LGD*LEE. EDF is replaced in some credit models with probability of default (PD). In the absence of information in estimating these complex measures, and with only the regulator's data on loan loss provisions, the expected loss can be crudely measured as an average of historical loss data of a bank's portfolio or of such portfolio's simulated loss data. The breaks however in the historical loss data (as measured by loss provisions) caused by changes in default definition and provision rates may render this approach less valid. This then leads to the second approach, that of simulation.

In the absence of such complete data on loans, an alternative would be to pool all classified loans of banks and draw random samples with the size determined by the total amount of bank's loan portfolio. Another alternative is to simulate the distribution of credit losses for a bank using its own pool of classified accounts.

In his study, Majnoni extracted a pool of loans and traced the status of the loan a year after. From this pool of loans, he randomly took sample of a predefined number of loans (500) and calculated the loss using a 50 percent predefined recovery ratio from face value of defaulted loan. However this approach is not applicable to Indonesian banking system since the current credit bureau can not trace the status of a loan from time to time.

Steps in bootstrap methodology are as follows:

Step 1: From the pool of classified accounts (loan with classification from special mention loans to loss loans) taken from credit bureau data, a random sample with predefined size of n (in this study n is the total number of classified accounts of the bank in consideration) was extracted.

Step 2: From this sample, total amount of provision was computed as the sum of the product of provision rate and the outstanding balance deducted by collateral value, that is:

$\text{provision}_i = \text{provision rate}_i \times (\text{outstanding balance - collateral value})$

Where provision rate = 1 percent, 5 percent, 15 percent, 50 percent and 100 percent depending on the classification of the account and i=1,2,3,...,n. n is the total number of classified account.
$\text{provision}_i" = \text{provision}_i/\text{outstanding balance}$

Step 3: Those two steps was repeated r times (with replacement). Since the concern is the estimation of the tail of the distribution, it is necessary to produce a large number of replicates such that 20,000 replications was used. This technique allows the replication of the risks faced by banks without specific knowledge or assumption regarding the correlation among different factors. However, without any assumed distribution, it will not be possible to simulate effects of shocks to specific factors affecting the default occurrences (Majnoni).

Step 4: From the simulated distribution, parameters such as the mean loss and variances was estimated and the maximum amount of losses that can be experienced from bank's classified accounts at 1 percent confidence level over the assumed time horizon was computed using the Value-at-Risk (VaR) concept. Then these 20,000 random drawn observations serve as the basis for getting the 95 percent and 99 percent quantile of the distribution. This upper value of distribution is the VaR value. Then this VaR figure is subtracted from the mean of provision resulting from bootstrap procedure to get the unexpected loss.

Since VaR is composed of both the expected and unexpected losses, the capital level, K_{cl}, that would be sufficient to cover banks' unexpected loss for classified accounts is given as VaR amount reduced by mean of bootstrapped provision.

Note that in the risk-based assessment of capital adequacy of a bank, the economic capital (accounting for credit risk alone) is determined by charging risk weights to almost all accounts (except sovereign accounts). However, for this study, only the classified accounts were considered hence, there is incomparability of K_{cl} with the regulatory capital that can be derived from the economic capital reported by the banks.

Note also that K should serve as benchmark in assessing the sufficiency of economic capital set aside by bank for credit risk. It should be seen as the minimum amount of capital that will cover unexpected losses even though K is estimated using the loan portfolio only, excluding other risk assets.

The estimated K was then compared with the actual economic capital for credit risk as reported by bank in its monthly report. Banks however are expected to account for other possible form of credit risk other than loan exposure including concentration risk.

3.2 Some Technical Notes on the Bootstrap Procedure

The most fundamental idea of the bootstrap method is the estimation of inference uncertainty from the estimated sampling distribution of the conceptual probability distribution *f*. In practical application, the bootstrap means using some form of re-sampling with replacement from the actual data, *x*, to generate B bootstrap samples, $\underline{x^*}$. Often the data (sample) consist of *n* independent units and it then suffices to take a simple random sample of size *n*, with replacement, from the *n* units of data, to get one bootstrap sample. However, the nature of the correct bootstrap data re-sampling can be more complex for more complex data structures.

The set of B bootstrap samples is a proxy for a set of B independent real samples from *f*. Properties expected from replicate real samples are inferred from the bootstrap samples by analyzing each bootstrap sample exactly as the real data sample is analyzed. From the set of results of sample size *B*, the inference uncertainty from sample to conceptual population is measured. The bootstrap can work well for large sample size (n), but may not be reliable for small n (say 5, 10, or even 20), regardless of how many bootstrap samples, *B*, are used (Efron, 1993).

The logic behind the bootstrap is this: All measures of precision come from a statistics' sampling distribution. The sampling distribution gives the relative frequencies of the values of the statistic when the statistic is estimated on a sample of size n from some population. The sampling distribution in turn, is determined by the distribution of the population and the formula used to estimate the statistic.

The benefits of applying bootstrap are as follows:

a. mimic the shape of the loss distribution function of any specific loan portfolio at a specific period of time

b. measure credit risk (including EL and UL) without identifying risk factor loadings, volatilities, correlations, etc.
c. minimize the impact of errors:
   (i) Model errors due to restriction representation on reality and
   (ii) Measurement errors on the estimation of the credit losses distribution function – model may rest on unobservable parameters that can only be approximated only with errors
d. enables replication of the real risk faced by banks without specific knowledge or assumptions regarding risk or correlation among different risk factors inherent in the actual credit loss distribution

In some cases, the sampling distribution can be derived analytically. For instance, if the underlying population is distributed normally, and one calculates the means, the sampling distribution for the mean is distributed as t with n-1 degrees of freedom. In other cases, deriving the sampling distribution is too hard, as in the case of means calculated from non-normal populations. Sometimes, as in the case of means, it is not too difficult to derive the sampling distribution as $n \rightarrow \alpha$. The distribution of means converges to a normal. The asymptotic result is then used to calculate some measure of statistical precision on a finite sample of size n even though it is incorrect.

Mechanically, the procedure is as follow: One has a dataset containing n observations and an estimator which, when applied to the data, produces certain statistics. One draws, with replacement, n observations from the n observation dataset. In this random drawing, some of the original observations will appear once, some more than once, and some, not at all. Using the dataset, one applies the estimator and estimates the statistics. One does it again, drawing a new random sample and re-estimating, and again, and keeps track of the estimated statistics at each step of the way (called a replication). In this study we use STATA and E-Views version 4.1. STATA is a general purpose statistical software package which is a command-based software. It provides high flexibility in the interactive mode, its programming features make it easy to conduct maximum likelihood estimation and matrix manipulation. E-Views is a general purpose econometrics (mathematics and statistics) package that able to conduct bootstrap non-parametric simulation procedure on the data.

4. Definition of Default

4.1 Default

Central Bank of Indonesia (BI) set factors in classification of credit quality based on prospects, debtor performance and repayment capability. Credit quality is classified as Current, Special Mention, Sub-Standard, Doubtful or Loss. Non-earning assets or non-performing loans are assets of the bank other than earning asset with potential for loss including but not limited to foreclosed collateral, abandoned property, interoffice accounts and suspense accounts, including loans categorized as Sub-Standard, Doubtful or Loss. A loan is non-performing subject to the following criteria:

a. **Prospects:** Business shows very limited or declining growth; relations with affiliated or group companies beginning to generate impacts that burden debtors; inadequate environmental management actions resulting to failure to meet minimum requirements stipulated in applicable laws and regulations or material breach to existing regulation.

b. **Debtor performance:** Business have very low earning or even suffer from loss, moderate to high debt-to-equity ratio, liquidity difficulties and business activity susceptible to changes in exchange rate and interest rates.

c. **Repayment Capacity:** There is outstanding debt or arrears in principal and/or interest exceeding 90 days. Repeated overdrafts incur mainly to cover operating losses and cash flow shortage. There is moderate to serious breach of key terms and conditions or covenant of credit.

In details, referring to Circular Letter No.7/3/DPNP as of 31 January 2005 regarding Asset Quality Rating for Commercial Banks, BI defines the categories according to the guidelines provided in *Annex 1.*

BI does not allow accrual of interest income for loans classified as non-performing (foreclosed collateral) as income until the income is realized. These non-performing loans are also subject to specific provisions depending on the number of days past due and security arrangements, if any. The summation of provisions made at different credit classification categories may be assumed to be equal to the overall expected loss that must be provided by bank. Basel II stipulates that bank should make its own estimate on expected loss for each or group of exposures.

Banks are required to set aside provision for asset loss in respect of earning assets and non-earning assets. The provision shall comprise of general reserves (at no less than 1 percent of current earning assets) and special reserves for earning assets and special reserves for non-earning assets. At the moment, provisions for asset losses that shall be set aside at least in accordance with the BI Regulation are as follows:

a. 5 percent of assets classified Special Mention, after deduction of collateral value;

b. 15 percent of assets classified Sub-Standard after deduction of collateral value;

c. 50 percent of assets classified Doubtful after deduction of collateral value;

d. 100 percent of assets classified Loss after deduction of collateral value;

On the other hand, loan and provision of funds in small amounts up to Rp500 million (around 50 thousand USD), small-scale business loan, loan and other provision of funds in business locations in specified regions to a limit of Rp1 billion (around 100 thousand USD) are exempted for the above mentioned loss provision. The quality classification then shall be based solely on prompt repayment of principal and/or interest.

The scope of the requirement for quality assessment of non-earning assets covers foreclosed collateral, abandoned property, interoffice accounts and suspense accounts. Types and values of collaterals eligible for deduction from provision for asset losses are stipulated as follows:

a. Securities and shares. If they actively traded on a stock exchange in Indonesia of rated investment grade, no more than 50 percent of the value recorded on the stock exchange at end of month.
b. Land, buildings, residential property, aircraft, marine vessels, motor vehicles and inventory, no more than:
 i. 70 percent of appraisal value if appraisal has been conducted during the last 12 months;
 ii. 50 percent of appraisal value, if appraisal was conducted more than 12 months but no more than 18 months previously;
 iii. 30 percent of appraisal value, if appraisal was conducted more than 18 months but no more than 24 months previously;

iv. 0 percent of appraisal value, if appraisal was conducted more than 24 months previously.

However BI reserves the right to recalculate the value of collateral set off against provision for asset losses if the bank fails to comply with the provisions.

Banks are also required to reappraise foreclosed collateral in order to determine net realizable value based on appraisal result from an independent body if the loan amount is above Rp5 billion (around USD500,000) or internal appraiser's report if the value of the foreclosed collateral is below Rp5 billion. If multiple values are obtained from independent appraisers or internal appraisers, then the lowest values shall be applied. Quality of foreclosed collateral for which resolution is pursued is as follows:

a. Current : if the foreclosed collateral has been held for up to 1 year

b. Sub-standard: if the foreclosed collateral has been held for more than 1 year and up to 3 years

c. Doubtful: if the foreclosed has been held for more than 3 years and up to 5 years

d. Loss : if the foreclosed collateral has been held for more than 5 years

Quality of any portion of earning assets such as loans that are backed by cash collateral shall be classified as Current and shall receive 0 percent risk weight. Collaterals that meet criteria of cash collateral are demand deposit, time deposit, saving deposit, guarantee deposit, gold, Bank Indonesia' certificate (issued by central bank act also as monetary operation instruments) or government securities, blanket guarantee of the Government of Indonesia in accordance with the applicable laws and regulations, standby letter of credit from prime bank issued under applicable Uniform Customs and Practice for Documentary Credits (UCP) or International Standby Practice (ISP).

Banks then are required to maintain their Capital Adequacy Ratio (CAR) higher or equal to minimum level of 8 percent commencing from the end of year 2001. Any banks unable to meet the minimum CAR level shall be placed under special surveillance. CAR level is calculated by dividing the sum of Tier 1 and Tier 2 capital to total amount of risk weighted assets (*on balance sheet and off balance sheet*) which commensurate the credit risk and also market risk in bank's portfolio. Risk weighted assets are determined by multiplying the nominal value of the assets concerned. The detailed list of earning asset's risk weight is elaborated in *Annex 2*.

Basel II, on the other hand, states that a default occurs when (1) the bank considers that an obligor is *unlikely to pay* its credit obligations to the bank in full, without recourse by the bank to actions such as realizing security or (2) the borrower is past due for more than 90 days on any material credit obligation to the bank.

Unlikely to pay is evidenced by (1) *The bank puts the credit obligation on non-accrued status*; (2) the *bank makes a charge-off or account-specific provision resulting from a significant perceived decline in credit quality subsequent to the bank taking on the exposure*; (3) the bank sells the credit obligation at a material credit-related economic loss;(4) t*he bank consents to a distressed restructuring of the credit obligation where this is likely to result in a diminished financial obligation caused by the material forgiveness, or postponement, of principal, interest or (where relevant) fees*; (5) the bank has filed for the obligor's bankruptcy or a similar order in respect of the borrower's credit obligation to the bank; and (6) the borrower has sought or has been placed in bankruptcy or similar protection where this would avoid or delay repayment of the credit obligation to the bank.

Although the number of days past due is not strictly aligned under BI's definition of NPL and Basel II definition of default, most of the other criteria for a default occurrence are exactly the same as highlighted above.

5. Data and Data Issues/Limitations

5.1 Data Issues/Limitations

Credit risk models apply its credit risk parameters on all outstanding exposures as of the period being considered, that is September 2005. Hence the result should not be interpreted as average values that represent credit risk exposures over different time horizon nor full economic cycle. Instead the result only reflects a snap-shot of credit risk condition in particular period.

The information available for this study is limited to the classified accounts hence the estimated economic capital will surely be an underestimate of the economic capital for the entire bank. Underestimation arises from the exclusion of other risk assets in the computation. The exclusion of these risk assets is made due to the impurity of these accounts i.e. other risk asset accounts are a combination of different exposures which may have different credit risk profiles. In addition, the lack of existing guidelines set to classify these other risk assets introduces non-sampling error that can not be quantified. Other data limitation of the study is the unavailability of static or frozen obligor pool to trace down loan status from year to year such that used by rating agency in developing transition matrices. There is also no enough information whether the loans had been written off from bank's book.

6. Results

The sample consists of 4 banks (3 percent from 131 total Indonesian commercial banks) that are considered being systemically important to Indonesian financial system, which represents 31.2 percent of total asset of all banks and 32.2 percent to total loans of the industry as of September 2005. The pool data consist of 545.780 data retrieved from credit bureau as of September 2005. The sample banks are medium to big sized commercial banks including state-owned and private banks. The NPLs ranged from 2 percent to 22 percent with average NPL gross ratio of 10.7 percent and NPL net ratio as of 6.7 percent. The CAR level of these sampled banks is quite high, with average CAR as of 17.1 percent. Table 2.3 provides selected information of sampled banks.

Table 2.3
Main Indicators of Sample Banks

Bank	Total Asset	Total Loan	Loan Propotion to Asset (%)	NPL (%)		CAR (%)
	(in million Rp)	*(in million Rp)*	a	Gross	Net	
1	47,344,738.0	19,574,436.0	41.3	2.9	2.0	13.74
2	39,095,237.0	27,649,197.0	70.7	6.1	4.3	17.19
3	242,156,589.0	99,343,863.0	41.0	21.8	14.1	21.97
4	113,928,165.0	72,297,285.0	63.5	12.0	6.3	15.69
	AVERAGE	**442,524,729.0**	**218,864,781.0**	**10.7**	**6.7**	**17.1**
	Total Bank's Asset	1,418,620,064.0				
	Total Bank's Loan		680,062,159.0			
	Percentage Sample to Population	31.2%	32.2%			

Table 2.4
Ratio of Classified Accounts to Total Loan Portfolio and Total Assets

Bank	% of Classified Accounts to Total Loan Portfolio	% Classified Accounts to Total Assets
1	9.5%	2.1%
2	16.4%	8.0%
3	46.1%	10.6%
4	17.4%	0.5%

The ratio of classified loans to total loan portfolio of the 4 banks under this study is ranging between 9.5 percent up to 46.1 percent. On the other hand the ratio of classified account to total asset spans from 0.5 percent to 10.6 percent.

Tables 2.5 and 2.6 provide some numerical description of the data on outstanding balances of classified accounts and provision for 4 banks under this study.

Table. 2.5
Summary Statistics on Outstanding Balances of Classified Account

Descriptive Statistics of Loan Outstanding				
				In million Rp
	Bank 1	**Bank 2**	**Bank 3**	**Bank 4**
No. of Observations	26,587.0	65,530.0	63,244.0	53,143.0
Mean	392.9	289.9	883.8	55.7
Standard Error	40.5	11.4	56.5	2.7
Median	54.1	66.6	47.9	15.7
Mode	0.00	0.00	0.00	0.0
Kurtosis	7214.7	2056.2	6510.6	8,049.9
Skewness	73.0	38.1	65.4	81.3
Range	760277.8	241976.6	1888543.1	70,042.6
Minimum	0.0	0.0	0.0	0.0
Maximum	760277.8	241976.6	1888543.1	70,042.6
Sum	10445813.1	18998773.4	55894643.3	2,957,548.2

Table 2.6
Summary Statistics on Provision Made for Classified Accounts

Descriptive Statistics of Provision

In million Rp

	Bank 1	Bank 2	Bank 3	Bank 4
No. of Observations	26,587	65,530	63,244	66.7
Mean	20.5	11.2	178.3	26.8
Standard Error	11.5	2.6	28.9	0.0
Median	0.5	0.0	0.5	0.0
Mode	0.0	0.0	0.0	6186.9
Kurtosis	24899.9	19472.8	39762.2	141.4
Skewness	155.7	129.8	182.1	1118768.8
Minimum	0.0	0.0	0	1118768.8
Maximum	301818.9	116535.2	1625862.1	3542465.6
Sum	545894.4	731212.9	11281122.3	53143.0

Figures 2.3 to 2.6 depict frequency distribution of classified loans in nominal amount extracted from population for 4 sample banks. The loan distribution is quite skewed to the right with skewness ranging from 38.1 to 81.3 indicating the normal distribution to the data may not be the appropriate approach. The loan concentration in Indonesia is more toward the small size loan, in which more than 45 percent of loans are less than Rp100 million (equivalent to $10,000).

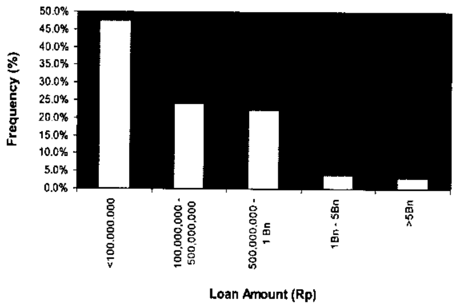


Figure 2.3. Frequency Distribution of Loan Outstanding of Bank 1

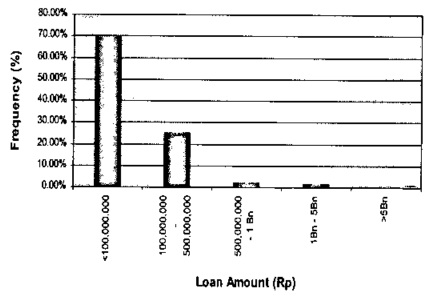


Figure 2.4. Frequency Distribution of Loan Outstanding of Bank 2

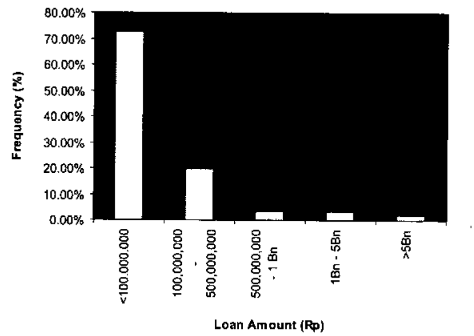


Figure 2.5. Frequency Distribution of Loan Outstanding of Bank 3

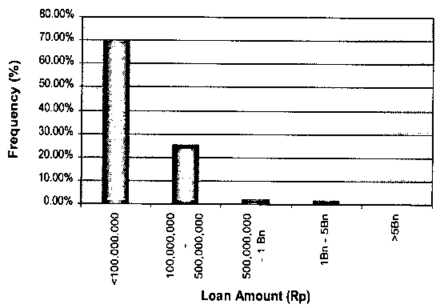


Figure 2.6. Frequency Distribution of Loan Outstanding of Bank 4

Figure 2.7 to 2.10 represent the frequency distribution of the loan provision for the sample's classified loans in nominal amount

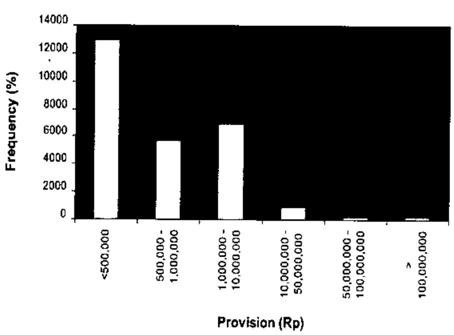


Figure 2.7. Frequency Distribution of Loan Provision of Bank 1

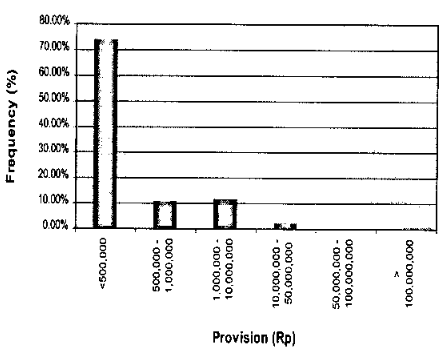


Figure 2.8. Frequency Distribution of Loan Provision of Bank 2

Figure 2.9. Frequency Distribution of Loan Provision of Bank 3

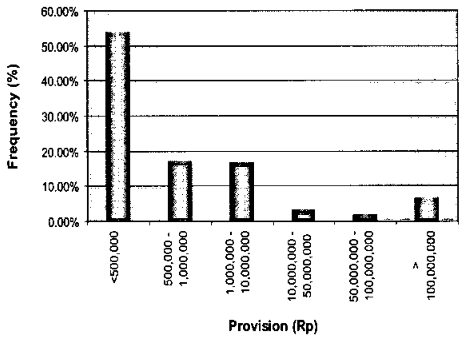


Figure 2.10. Frequency Distribution of Loan Provision of Bank 4

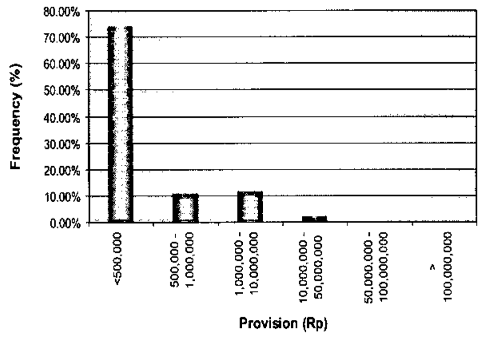


Figure 2.11 to 2.14 shows 20,000 randomly selected portfolio amounts of provision. After applying bootstrap simulation with replacement, the results then provide value of expected losses and unexpected losses and the values that capital and loan loss reserves need to achieve to protect banks from insolvency in 95 percent and 99 percent confidence level as required by Basel II.

Figure 2.11. Frequency Distribution of 20,000 Sums of Provision: Bank 1

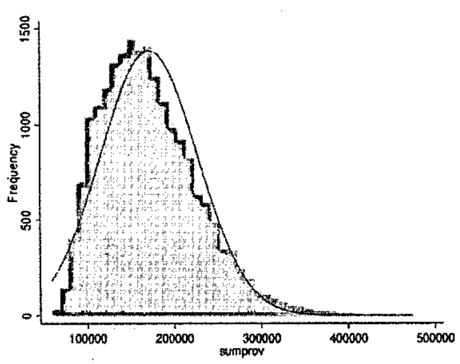


Figure 2.12. Frequency Distribution of 20,000

Sums of Provision: Bank 2

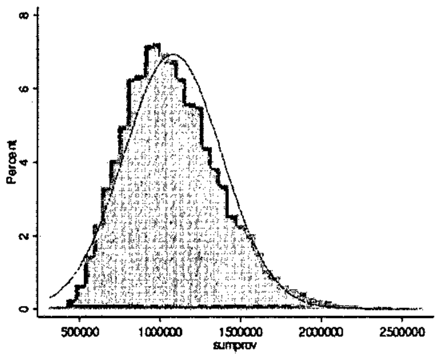


Figure 2.13. Frequency Distribution of 20,000

Sums of Provision: Bank 3

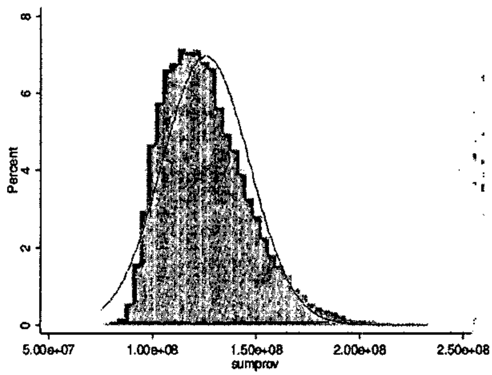
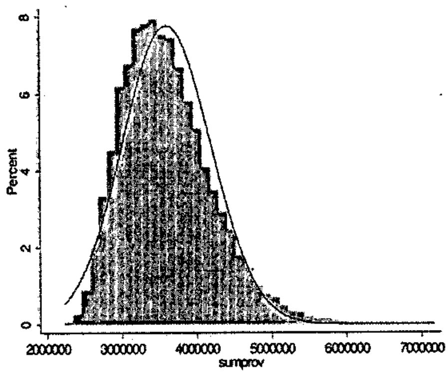


Figure 2.14. Frequency Distribution of 20,000

Sums of Provision: Bank 4



Simulated expected losses (EL) expressed as a fraction of the total loan portfolio ranges from 1.6 to as high as 22.5 percent (Table 2.7). This result is below the simple average of current Indonesian regulatory provision under Basel I regime at 55 percent. The EL number is assumed to be the provision to cover loan exposure.

The VaR values also expressed as a fraction of the total loan portfolio of the bootstrapped distribution at five and one percent significance level range from 2.8 percent to 38.5 percent and 3.1 to 41.5 percent, respectively.

The unexpected losses also expressed as a fraction of the total loan portfolio seemed to be underestimating the required overall capital at both significance levels. This is expected since the CAR value covers all risks faced by banks.

Table 2.7
Capital and Provisions Expressed in Percentage of the Total Loan Portfolio

Bank	VaR		EL	UL		CAR
	95%	99%		95%	99%	
Bank 1	2.8	3.1	1.6	1.1	1.4	13.7
Bank 2	10.6	11.7	5.7	3.8	5.0	17.2
Bank 3	38.5	41.5	22.5	9.5	12.5	22.0
Bank 4	18.3	19.7	12.2	4.5	5.9	15.7

Table 2.8
Capital and Provisions Expressed in Percentage of the Total Classified Accounts

Bank	VaR		UL		CAR
	95%	99%	95%	99%	
Bank 1	28.13	31.58	10.97	14.42	13.74
Bank 2	53.89	59.93	19.22	25.27	17.19
Bank 3	64.71	69.72	15.95	20.96	21.97
Bank 4	92.27	99.32	22.45	29.50	15.69

The bank with the lowest capital ratio required to cover UL based on simulation, is a national private bank whose shares have been bought by foreign companies. This bank also has the lowest CAR and NPL levels. It also requires lowest provision level to cover EL.

The bank with the highest K required to cover its UL also provides the highest level of EL, which is a state-owned bank which focuses its business in retail lending to small medium sized banks.

Retail loan is characterized by small exposure amounts (relative to the size of the bank) extended to a large number of borrowers. This type of loan normally has shorter maturity and supposedly low correlation among borrowers. Such a unique nature theoretically should have effect of reducing the capital requirements for retail loans compared to that of corporate lending. However, the NPL level of the bank is quite high with the gross NPL at 12.0 percent while the net NPL is at 6.3 percent, slightly higher than 5 percent threshold prerequisite of the BI.

From Table 2.7, we can derive that relative to the overall capital set aside by banks for its unexpected losses, there is no bank that meets the regulatory amount for classified accounts. However, a more appropriate comparison would be between the estimate and the required for classified accounts only.

Expressing UL as a percentage to total classified accounts measures the possible unexpected losses among classified accounts. One important caveat in analyzing the result of the simulation presented in Table 2.8 is that the simulation exercise limits itself to classified accounts only. Credit risk contributed by other earning assets including off-balance sheet items were not covered by the estimated K in the study. Hence underestimation will necessarily be an outcome.

7. Conclusion and Recommendation

This simulation exercise using classified accounts assumes that provision is a good measure of expected losses of a bank. Results show that unexpected losses expressed as a percentage of the total loan portfolio would be underestimated using data on provision alone. However, expressing the estimate as a fraction of the total classified accounts only provides an opposite picture. This measure however should not be compared to the overall capital required of banks since it only measures the unexpected losses that can be realized from classified accounts only. A more appropriate comparison would be between this estimate and that of the required capital for classified accounts.

Crude as it is at this level this method can be used as additional tool for regulator in bank supervision or even by banks to complement its credit risk management system and risk based capital calculation as mandated by Basel II. Special surveillance should be applied to banks with higher UL that has not been covered by current capital level.

On the VaR being the sum of expected and unexpected losses, a proper comparison would be between the overall VaR and the sum of provisions and capital set aside by banks.

To get a more robust conclusion from this exercise, the procedure needs to be applied to more banks and if possible, to historical data on bank losses. Moreover, the procedure needs to be applied also to data acquired during the boom and recession periods.

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ANNEX 1

Appendix I, Circular Letter of Bank Indonesia No. 7/ 3 /DPNP dated January 31, 2005

CLASSIFICATION OF ASSET QUALITY

	PROSPECTS				
COMPONENT	**CURRENT**	**SPECIAL MENTION**	**SUB-STANDARD**	**DOUBTFUL**	**LOSS**
Growth potential	■ Business has strong growth potential.	• Business has limited growth potential.	■ Business shows very limited growth potential or is not growing.	■ Business is in decline.	• Survival in serious doubt, difficult to restore viability. • Strong likelihood that business will come to end.
Market conditions and position of debtor in relation to competition	■ Stable market, not influenced by changes in economic conditions. • Limited competition, among those with strong market position. • Operating at optimum capacity.	■ Good market position, not strongly influenced by changes in economic conditions. • Market share on par with competitors. • Operating at almost optimum capacity.	■ Market influenced by changes in economic conditions. • Market position fair, but has many competitors, nevertheless able to recover with implementation of new business strategy. • Not operating at optimum capacity.	• Market strongly influenced by changes in economic conditions. • Fierce competition, company operations in serious trouble. ■ Capacity not at level capable of supporting operations.	• Loss of market as economic conditions decline. • Operations not on continual basis.
Management quality and labor problems	• Excellent management. • Adequate manpower levels with no record of disputes or strikes, or past disputes/ strikes that were nevertheless properly resolved.	• Good management. ■ Generally adequate manpower levels, past disputes or strikes properly resolved but could possibly break out again.	• Fairly good management. • Surplus level of manpower and ongoing disputes/strikes with fairly material impact on the business of debtor.	Inexperienced management. • Excessively high manpower level and attendant risk of unrest, ongoing disputes/strikes with fairly material impact on business of debtor.	• Weak management. • Extremely high level of excessive manpower and attendant risk of unrest, ongoing disputes/strikes with material impact on business of debtor.

PROSPECTS					
COMPONENT	CURRENT	SPECIAL MENTION	SUB-STANDARD	DOUBTFUL	LOSS
Support from group or affiliates	• Affiliated or group companies stable and support business operations.	• Affiliated or group companies stable and not generating impacts that burden debtor.	• Relations with affiliated or group companies beginning to generate impacts that burden debtor	■ Affiliated or group companies generating impacts that burden debtor.	■ Affiliated company incurring serious losses for debtor.
Measures taken by the debtor to conserve the environment (for large-scale debtors with major impact on environment)	• Good environmental management actions, results at least meeting the minimum requirements stipulated in applicable laws and regulations.	• Inadequate environmental management actions, results failing to meet minimum requirements stipulated in applicable laws and regulations.	■ Inadequate environmental management actions, results failing to meet minimum requirements stipulated in applicable laws and regulations, material irregularities.	• Company failing to take significant environmental management actions, or has taken management actions but failing to meet minimum requirements stipulated in applicable laws and regulations, material irregularities.	■ Company failing to take significant environmental management actions, or has taken management actions but failing to meet minimum requirements stipulated in applicable laws and regulations, and faces possible prosecution.

DEBTOR PERFORMANCE					
COMPONENT	**CURRENT**	**SPECIAL MENTION**	**SUB-STANDARD**	**DOUBTFUL**	**LOSS**
Earnings	■ High, stable earnings.	• Fairly good earnings but with potential for decline.	• Low earnings.	• Very low or negative earnings. ■ Operating losses financed by sale of asset.	• Sustaining heavy losses. • Debtor unable to meet all liabilities and business is unsustainable.
Capital structure	■ Strong capital.	• Fairly good capital, owners have capability to provide additional capital if needed.	• Moderate debt-to-equity ratio.	• High debt-to-equity ratio.	■ Extremely high debt-to-equity ratio.
Cash flow	• Strong liquidity and working capital. • Cash flow analysis shows that debtor is able to meet principal and interest obligations without support from additional sources of funds.	• Generally good liquidity and working capital. ■ Cash flow analysis shows that although debtor is able to meet principal and interest obligations, indications exist of certain problems that left unresolved will affect future payments.	• Low liquidity and limited working capital. • Cash flow analysis shows that debtor is only able to repay interest and part of principal.	• Very low liquidity. • Cash flow analysis shows inability to repay principal or interest. • New borrowings used to rollover obligations falling due and payable.	• Liquidity difficulties ■ Cash flow analysis shows that debtor is unable to cover production costs. ■ Material use of new borrowings to rollover obligations falling due and payable.
Sensitivity to market risks	■ Relatively little of portfolio sensitive to changes in exchange rate and interest rates or portfolio has proper hedging.	• Some of portfolio sensitive to changes in exchange rate and interest rates, but still within controllable limits.	• Business activity susceptible to changes in exchange rate and interest rates.	• Business activity threatened by changes in exchange rate and interest rates.	• Business activity threatened by fluctuation in exchange rate and interest rates.

REPAYMENT CAPACITY

COMPONENT	CURRENT	SPECIAL MENTION	SUB-STANDARD	DOUBTFUL	LOSS
Promptness in repayment of principal and interest	• Prompt repayment, positive progress in loan account, no arrears, compliance with credit terms and conditions.	• Arrears in principal and/or interest of up to 90 (ninety) days. • Overdrafts seldom.	• Arrears in principal and/or interest exceeding 90 (ninety) days but no more than 120 (one hundred and twenty) days. • Repeated overdrafts, mainly to cover operating losses and cash flow shortage.	• Arrears in principal and/or interest exceeding 120 (one hundred and twenty) days but no more than 180 (one hundred and eighty) days. ■ Overdraft is permanent, mainly to cover operating losses and cash flow shortage.	• Arrears in principal and/or interest exceeding 180 (one hundred and eighty) days.
Availability and accuracy of financial information on the debtor	• Debtor relationship with bank is good, debtor always provides accurate financial information on regular basis. ■ Latest financial statement is available with Bank analysis of financial statement/ financial information provided by debtor.	■ Debtor relationship with bank is fairly good, debtor always provides financial information on regular basis and information is still accurate. • Latest financial statement is available with Bank analysis of financial statement/ financial information provided by debtor.	• Debtor relationship with bank is deteriorating and financial information is unreliable or no Bank analysis of financial statement/ financial information provided by debtor.	■ Debtor relationship with bank is steadily deteriorating and financial information is unavailable or unreliable.	■ Debtor relationship with bank is very poor and financial information is unavailable or unreliable.
Completeness of credit documentation	• Complete documentation of credit.	• Complete documentation of credit.	• Inadequately complete documentation of credit.	• Incomplete documentation of credit.	• No documentation of credit.
Compliance with credit agreement	• No breach of credit agreement.	• Minor breach of credit agreement.	• Moderate breach of key terms and conditions of credit.	• Major breach of key terms and conditions of credit agreement.	• Extremely serious breach of key terms and conditions of credit agreement.

REPAYMENT CAPACITY					
COMPONENT	**CURRENT**	**SPECIAL MENTION**	**SUB-STANDARD**	**DOUBTFUL**	**LOSS**
Appropriate-ness of use of funds	■ Use of funds consistent with loan application. • Amount and type of facility appropriate to need. • Credit term extension consistent with analysis of debtor needs.	• Use of funds less consistent with loan application, but not in material amount. • Amount and type of facility greater than needed, but not in material amount. • Credit term extended not fully in accordance with analysis of debtor needs.	• Use of funds less consistent with loan application, in fairly material amount. • Amount and type of facility greater than needed, in fairly material amount. • Credit term extended not according to analysis of debtor needs (term extension to conceal financial difficulties).	■ Use of funds less consistent with loan application, in material amount. • Amount and type of facility greater than needed, in material amount. • Credit term extended not according to analysis of debtor needs (term extension to conceal financial difficulties) with major irregularities.	• Use of funds mostly in departure from loan application. • Amount and type of facility greater than needed, in very material amount. ■ Credit term extended without analysis of debtor needs.
Viability of source for payment of obligations	■ Source of payment clearly identifiable and agreed by bank and debtor. • Source of payment appropriate to structure/type of borrowing. • Viable repayment scheme (includes any provision of grace period). ■ Foreign currency revenues sufficient to support repayment foreign currency of credit.	■ Source of payment identifiable and agreed by bank and debtor. • Source of payment less appropriate to structure/type of borrowing. • Fairly viable repayment scheme (includes any provision of grace period). • Foreign currency revenues less than sufficient to support repayment foreign currency of credit.	• Payment originating from source other than agreed. • Source of payment materially less appropriate to structure/type of borrowing. ■ Repayment scheme is insufficiently viable, grace period is provided that is not appropriate to type of credit. • Foreign currency revenues materially insufficient to support repayment of foreign currency credit.	• Source of payment not known, while agreed source is no longer viable. ■ Source of payment materially inappropriate to structure/type of borrowing. • Repayment scheme is insufficiently viable, long grace period is provided that is not appropriate to type of credit. • Foreign currency revenues materially insufficient to support repayment of foreign currency credit.	• No possible source of repayment. • Source of payment completely inappropriate to structure/type of borrowing. • Repayment scheme is not viable, long grace period provided that is not appropriate to type of credit. • No foreign currency revenues to support repayment of foreign currency credit.

ANNEX 2

CALCULATION OF RISK-WEIGHTED ASSETS FOR EARNING ASSETS ACCOUNTS

(in millions of rupiahs)

Appendix to Circular Letter of Bank Indonesia No. 2/12/DPNP dated June 12, 2000

COMPONENT	percent Risk	Nominal Value	Special Provisioning *)	Book Value
A. BALANCE SHEET ASSETS (Rupiahs and foreign currencies)				
1. Claims on other banks:				
1.1 on central banks of other countries	0			
1.2 on other banks, guaranteed by the central govt or central bank	0			
1.3 on other banks	20			
2. Securities held:				
2.1 Bank Indonesia Certificates	0			
2.2 Treasury Bills of other countries	0			
2.3 Central bank certificates of other countries	0			
2.4 Money market/capital market securities, etc.				
2.4.1. issued or guaranteed by the central hank or central gov't	0			
2.4.2. issued and guaranteed by cash, foreign banknotes, gold, gold currency, and demand deposits, time deposits, and savings deposits at the hank concerned in the amount of the guaranteed value	0			
2.4.3. issued or guaranteed by other banks, regional governments, statutory agencies in Indonesia, and Multilateral Development Banks	20			
2.4.4. issued or guaranteed by national state owned enterprises, and corporations owned by central governments of other countries	50			
2.4.5. issued or guaranteed by other private parties	100			
3. Credit:				
3.1 Loans provided or guaranteed by:				
3.1.1. the central hank	0			
3.1.2. the central government	0			
3.1.3. cash, foreign banknotes, gold, gold currency, and demand deposits, time deposits, and savings deposits at the hank concerned in the amount of the guaranteed value	0			
3.1.4. other banks, regional governments, statutory agencies in Indonesia, Multilateral Development Banks	20			
3.1.5. national state enterprises, and corporations owned by central governments of other countries	50			
3.1.6. other parties	101)			
3.2 Home mortgages guaranteed by first hypothec for own use	50			
4. Equity participation	100			

CALCULATION OF RISK-WEIGHTED ASSETS FOR EARNING ASSETS ACCOUNTS in millions of rupiahs

Appendix to Circular Letter of Bank Indonesia No. 2/12/DPNP dated June 12, 2000

COMPONENT	percent Risk	Nominal Value	Special Provisioning *)	Book Value
B. OFF-BALANCE SHEET ACCOUNTS (rupiahs and foreign currencies)				
1. Bank guarantees				
1.1 for loans, including standby L/Cs, risk-sharing, and endorsement or securities issued upon application of:				
1.1.1. the central bank and central gov't	0			
1.1.2. other banks, regional governments, statutory agencies in Indonesia, and Multilateral Development Banks	20			
1.1.3. national state owned enterprises, and corporations owned by central governments of other countries	50			
1.1.4. other parties	50			
1.2 not for loans, such as bid bonds, performance bonds, and advance payment bonds issued upon application of:				
1.2.1. the central bank and central government	0			
1.2.2. other banks, regional governments, statutory agencies in Indonesia, Multilateral Development Banks	10			
1.2.3. national state owned enterprises, and corporations owned by central governments of other countries	25			
1.2.4. other parties	50			
1.3 Current L/Cs (not including standby L/Cs) issued upon application of:				
1.3.1. the central bank and central government	0			
1.3.2. other banks, regional governments, statutory agencies in Indonesia, Multilateral Development Banks	4			
1.3.3. national state owned enterprises, and corporations owned by central governments of other countries	10			
1.3.4. other parties	20			
2. Liabilities for repurchase of bank assets sold under repurchase agreements	100			

*) Special provisioning is defined as Allowance for Earning Assets Losses formed for earning assets rated as Special Mention, Sub-standard, Doubtful, and Loss.

CHAPTER 3
ADEQUACY OF THE EXISTING LEVELS OF CAPITAL IMPLIED BY THE BASEL STANDARDS, RELATIVE THE CREDIT EXPOSURES OF BANKS IN THE PHILIPPINES

by
Marissa L. Barcenas[3]

1. Introduction

The revised framework for capital measurement as proposed by the Basel Committee on Banking Supervision (BCBS) is designed to make the existing risk-based capital adequacy framework more risk sensitive. For credit risk in particular, it introduced two (2) basic approaches by which banks may compute their capital requirements that are deemed more reflective of the level of risk in their portfolios. The first approach, the standardized approach, requires the use of external credit rating agencies' assessments in order to determine the required capital for assumed portfolios. The second approach, the internal ratings based approach, determines default probabilities through the use of internal ratings and uses a complex credit risk algorithm which is a function of the default probabilities and other parameters to estimate capital requirements.

Despite its seeming complexities, most banking supervisory bodies in the SEACEN region have signified their intention to adopt the new framework more commonly known as Basel II. The region however may encounter difficulties in adopting these two approaches. For one, majority of bank portfolios in the region are un-rated and lacking in market quoted claims. Second, the set of procedures embedded in the IRB approach may be difficult to implement due primarily to the possible mismatch of the level of sophistication and resources available in the region with that of the G10 counterparts that serve as basis for calibrating the complex credit risk algorithm of the IRB approach. For example, many SEACEN countries lack credit bureaus or if there is any, the information contained therein is very limited. As such, whatever detailed and richer information available at the bank may not be available to supervisors. In fact for most of the supervisors, the only data available are bank level data found in financial statements.

1. Bank Officer III, Office of Supervisory Policy Development, Bangko Sentral ng Pilipinas

Due to these limitations, the intention is to adopt these approaches on a gradual basis until 2010. On the interim however, how can supervisors assess the adequacy of existing levels of capital implied by the Basel Standards relative to the credit risk exposures of banks in the SEACEN Region? This paper therefore proposes two approaches in measuring credit risk using current available information such as the list of classified accounts based on on-site supervisory examinations. Both approaches use re-sampling technique in order to estimate the credit loss distribution. The first approach used provision as a measure of expected losses. The second approach used a measure of Loss Given Default (LGD) rate to estimate the expected loss from each of the defaulting loans among the classified accounts.

This paper has six (6) sections including this section. Section two (2) gives some highlights on the Philippine Banking System. Section three (3) presents the data and their limitations. Section four (4) discusses the methodology used in the study. Section five (5) presents the results and section six (6) gives the conclusion derived from the study.

2. The Philippine Banking System[4]

As at end December 2005, the Philippine banking system has 7,670 banks 4,318 of which are universal and commercial banks, 1,293 are thrift banks, and 2,059 are rural and cooperative banks.

Resource-wise, universal and commercial banks represent the largest single group of financial institutions in the country. They command the biggest market share of 89.3 percent, 4.7 percent of which are due from foreign banks. These banks offer the widest variety of banking services among financial institutions. In addition to the function of an ordinary commercial bank, universal banks are also authorized to engage in underwriting and other functions of investment houses, and to invest in equities of non-allied undertakings.

The thrift banking system is composed of savings and mortgage banks, private development banks, stock savings and loan associations and microfinance thrift banks and has a market share of eight (8.0) percent. Thrift banks are engaged in accumulating savings of depositors and investing them. They also provide short-term working capital and medium- and long-term financing to businesses en-

1. www.bsp.gov.ph

gaged in agriculture, services, industry and housing, and diversified financial and allied services, and to their chosen markets and constituencies, especially small- and medium- enterprises and individuals.

The remaining 2.7 percent of the total banking sector asset is due from rural and cooperative banks. These banks are the more popular type of banks in the rural communities. Their role is to promote and expand the rural economy in an orderly and effective manner by providing the people in the rural communities with basic financial services. Rural and cooperative banks help farmers through the stages of production, from buying seedlings to marketing of their produce. Rural banks and cooperative banks are differentiated from each other by ownership. While rural banks are privately owned and managed, cooperative banks are organized/owned by cooperatives or federation of cooperatives.

Of the risks faced by banks, the greatest is credit risk as loan portfolio accounts for almost half the total assets of banks.

Banks are examined at least twelve months apart by the Bangko Sentral ng Pilipinas (BSP) examiners. BSP acts as the central bank of the Republic of the Philippines.

3. Data and Data Limitations

Re-sampling technique requires data on per account level to be able to measure the standard error of the distribution of credit losses. Currently, the only data available to BSP on per account basis are the classified accounts listed in the Report of Examination (ROE) prepared by bank examiners. While it is recognized that assets other than loan portfolio of banks contribute to total credit risk faced by banks, the lack of required details and the complexity of the risks on other assets delimit the study to using only loan accounts – more specifically classified accounts. The unclassified are also not available on per account level but they definitely contribute to credit risk.

Examiners use five categories for classified accounts. These categories are linear ordering of creditworthiness of the accounts which are determined based on several conditions including the number of days past due set by the BSP. See Annex 1 for the guidelines set by the BSP in classifying accounts into the following categories:

Category	Classification	Provision in Percent
1	Specially Mentioned (LEM)	5
2	Substandard Secured	10
3	Substandard Unsecured	25
4	Doubtful	50
5	Loss	100

Although this may be seen as somewhat similar to credit grading for defaulted accounts, the lack of credit bureau that maintains historical record of these accounts poses several limitations in using any model-based methodology. For one, there is no complete record of all accounts hence it is very difficult to establish probabilities or likelihood of the exposure moving from one classification to the other.

Provision for these accounts depends on the number of days past due and security arrangements, if any. It should be noted however that some accounts classified as specially mentioned were classified not because of delay or failure of the counterparty to meet his obligation but due to some potential weaknesses that deserve management's close attention. These potential weaknesses, if left uncorrected, may affect the repayment of the loan and thus increase credit risk of the bank. Other than these accounts, the rest can be termed as non-performing loans.

Non-performing loans (NPL) as defined by the BSP are those loans that are (a) unpaid for thirty (30) days or more after due date or after they have become past due (for loans payable in lump sum, or in quarterly, semi-annual or annual installments); (b) have three (3) or more installments in arrears (for loans payable in monthly installments); and; (c) are restructured (subject to certain criteria).

BSP does not allow accrual of interest income for loans classified as non-performing.

Basel II states that a default occurs when (a) the bank considers that an obligor is *unlikely to pay* its credit obligations to the bank in full, without recourse by the bank to actions such as realizing security or (b) the borrower is past due for more than 90 days on any material credit obligation to the bank.

Unlikely to pay is evidenced by (a) *The bank puts the credit obligation on non-accrued status*; (b) the *bank makes a charge-off or account-specific provision resulting from a significant perceived decline in credit quality subsequent to the bank taking on the exposure*; (c) the bank sells the credit obligation at a material credit-related economic loss;(d) t*he bank consents to a distressed restructuring of the credit obligation where this is likely to result in a diminished financial obligation caused by the material forgiveness, or postponement, of principal, interest or (where relevant) fees*; (e) the bank has filed for the obligor's bankruptcy or a similar order in respect of the borrower's credit obligation to the bank; and (f) the borrower has sought or has been placed in bankruptcy or similar protection where this would avoid or delay repayment of the credit obligation to the bank.

Although the number of days past due is not strictly aligned under BSP definition of NPL and Basel II definition of default, most of the other criteria for a default occurrence are exactly the same as italicized above.

The first approach used the data on provision for all classified accounts including LEM accounts that are current on the assumption that provision is a good measure of expected losses. The second approach used only those that are classified in categories two (2) to five (5) and an LGD rate estimated from the sale of Non Performing Assets (NPA) under the Special Purpose Vehicle Act[5] to be consistent with the ageing period of Basel II default.

4. Methodology

4.1 Measuring Credit Risk

Credit risk is the risk of loss on a financial or non-financial contract due to the counterparty's failure to perform on that contract. Credit risk's two components are default risk and recovery risk. Default risk is the possibility that a counterparty will fail to meet its obligation, and recovery risk is the possibility

5. Special Purpose Vehicle Act (RA 9182) is an Act granting tax exemptions and fee privileges to special purpose vehicles which acquire or invest in non-performing assets, setting the regulatory framework thereof, and for other purposes.

that the recovery value of the defaulted contract may be less than its promised value.

Most commonly used methodologies to measure distribution of credit losses are model based. Models that try to measure credit risk can be classified into four groups: the spot rate models, default models, credit rating models and asset models. These classifications group credit risk models according to how they explicitly or implicitly describe the default and recovery rate process. Most of the models however focus on modeling default rather than recovery.

Spot rate models. This first division of models attaches a price to credit risk and the dynamics of default is implied by the dynamics of the price of credit risk. The price of the credit risk is reflected in any of the credit risk spot rate, forward rate, or discount factor. These models focus on one of these three rates.

Default models. Models of this type directly model the risk of default and are closely related to the spot rate models.

Credit rating models. Credit rating models generalize default models. If in default models there are only two states, default and non-default, in these types of models, there is a state for each credit rating. The credit rating system is a linear ordering of creditworthiness. The rating could be assigned by a credit rating agency, implied by market prices of the firm's debt, or calculated or assigned through some other means. The lowest state usually represents default.

Asset model. This approach is a continuous state limit of the credit rating approach as exemplified by Black-Scholes and Merton model. In this approach, it is deemed that the corporation's asset is the sum of its equity and debt. The firm goes into default when the value of the assets drops below the face value of the debt. Viewed this way, both the equity and debt are contingent claims on the total assets of the firm and their prices were modeled using the Black-Scholes and Merton option theory.

Examples of the default models and credit rating models are the KMVs Credit Monitor and JP Morgan's CreditMetrics, respectively. These are the models used in more developed jurisdictions and are largely based on equity or corporate bond prices. Both approaches however, have as their foundation Merton's asset value model which establishes a relationship between credit quality and asset value of the debtor firms. In Credit Monitor, the volatility of equity prices are used as inputs in determining the "distance to default", which is the difference between the value of a company's assets and a certain liability threshold. CreditMetrics, on the other hand, is a *marked-to-market* approach, which links bond prices and ratings, and the probability distribution of future bond prices, and hence a description of credit risk, are calculated based on a ratings transition matrix.

Another default model is the CreditRisk+ used by Balzarotti et. al. (2002). Balzarotti used data from Argentina's *Central de Deudores* database, a public credit registry, in measuring credit risk in Argentine banks' loan portfolio.

Default models work well in jurisdictions with liquid equity markets. The applicability of this approach therefore, is limited in the SEACEN region. In addition, the default experiences of big corporate entities that characterize the equity markets are not reflective of the default scenario of SEACEN banks' loan portfolio, which are composed mostly of lending to the small and medium businesses. Balzarotti was able to use a default model given a small universe of quoted equities and a small number of rated and traded corporate bonds but with the use of a public credit registry. Public credit registries however, are either not existing or are wanting in terms of needed information in most SEACEN countries.

Credit rating models on the other hand, works well in markets with big pools of rated corporate bonds. The dearth of rated bond issuances in the region makes this approach not suitable for measuring credit risk in the banking system. Besides, those that issue bond instruments are mostly big companies, which again are not representative of the banking system's credit risk exposures.

In the absence of information in estimating complex model measures, and with only the regulator's data on classified accounts, expected loss of a loan portfolio can be crudely measured as the summation of all provisions made at different credit classification categories. This is with the assumption that provisioning standards are adequately measuring the risk involved in each classification. To establish the distribution of credit losses, there is a need to collect historical data on provisions. The breaks however in the historical loss data (as measured by loss provisions) caused by changes in provision rates may render this approach less valid (See Annex 1 for the changes in the provisioning rates applied to some classifications). Another approach would be through simulation.

Several simulation procedures are available that can be classified as either parametric or non-parametric. Two of these approaches are the jackknife and the bootstrap. The bootstrap is a computer-intensive method developed by Bradley Efron and others to derive standard errors of estimates from information in the sample and do statistical inference (see Annex 2 for technical description of bootstrap). Bootstrap was adopted by Majnoni (2004) in estimating bank capital and in setting loan loss reserve regulation in his paper entitled "Bank Capital and Loan Loss Reserves Under Basel II: Implications for Emerging Countries". In this paper however, Majnoni used data from a public credit registry that contains information on a very large number of loans in the financial systems of Argentina, Mexico and Brazil.

In the absence of such complete data on loans, this study made use of the list of classified accounts as found in ROEs. Pooling of classified accounts for all banks was not resorted to due to the differing reporting periods of ROEs. The credit loss distribution was estimated using either the data on provision for classified accounts or by applying an estimated LGD to all classified accounts that were past due for at least 90 days (defaulted loans).

Simulation was done in this manner:

(1) Using the data on provision (Approach 1): from the pool of classified accounts, a random sample of size n (n can be the total number of classified accounts of the bank in consideration) was taken (Step 1). From this sample, the total amount of provision was computed (Step 2). These two steps were repeated r times using STATA software. Since the concern was the estimation of the tail of the distribution, it was necessary to produce a large number of replicates such that r was set at 20,000. This technique allowed the replication of the risks faced by banks without specific knowledge or assumption regarding the correlation among different factors. However, the lack of an underlying model precludes simulation exercises based on shocks to specific factors (Majnoni).

(2) Using LGD estimate (Approach 2): LGD rate was measured based on the sale of Non-Performing Assets (NPAs) by the SPVs. Data show that an LGD rate of approximately 73 percent was realized from the sale of NPAs. Using this figure, expected loss of the loan portfolio was estimated as the product of LGD rate and the outstanding balance of those that are classified in categories 2 to 5 (defaulted loans). Note that the probability of default for categories 2 – 5 is one, hence expected losses is measured as the product

of LGD rate and outstanding balance. The resulting data set of expected losses was taken as the initial sample from which re-sampling was done to generate the distribution of credit losses. That is, a sample of size n was taken r times with the sum of expected losses computed for every replicate.

From each of the simulated distribution, parameters such as the mean loss and variances were estimated and the maximum amount of losses that can be experienced from bank's classified accounts at five (5) percent, one (1) percent and 0.1 percent confidence level over the assumed time horizon was computed using the Value-at-Risk (VaR) concept. Since VaR is composed of both the expected and unexpected losses, the capital level, K_{cl}, that would be sufficient to cover banks' unexpected loss for classified accounts was derived by subtracting the expected loss from the VaR value.

Note that in the current risk-based assessment of capital adequacy of a bank in the country, the minimum capital (K_R) to cover for credit risk is determined by multiplying the risk weighted assets with 10 percent. Risk weights ranging from 20 percent to 125 percent, are assigned to almost all accounts except those that are guaranteed by or collateralized by securities issued by the Philippine national government, the BSP and central government and central banks of foreign countries with the highest credit quality and multilateral banks. Zero risk weight is applied to loans to the extent covered by hold out on, or assignment of deposit/ deposit substitutes maintained with the lending bank, or loan guarantee funds.

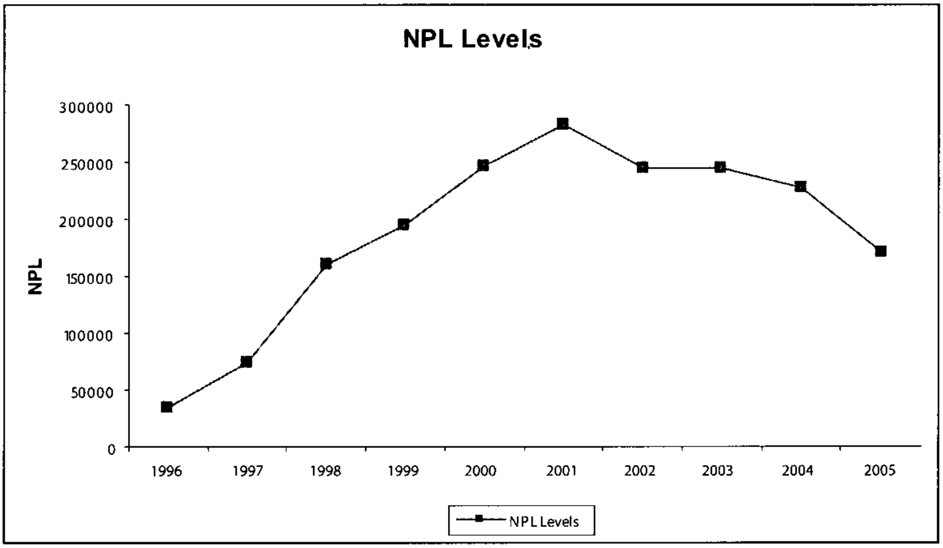
NPLs were currently assigned risk weight of 75 or 125 percent depending on the purpose of the loan. Non-performing loans for housing purposes fully secured by first mortgage on residential property (NPL_H) are given risk weight of 75 percent while all other nonperforming loans (NPL_A) are given risk weight of 125 percent.

The methodology was initially tested using the data of the nine commercial banks chosen from the 41 commercial banks in the country. A bank was selected on the basis of sufficiency of the number of its classified accounts to use in the simulation.

5. Results

Figure 3.1 below gives the trend in the levels of total NPL in the Philippine banking system. Even before being hit by the financial crisis in 1997, the levels of NPL in the Philippines has been on an uptrend reaching its peak in 2001. It started to decline since then with the biggest year-on-year decline experienced in 2005, at the end of the implementation of the Special Purpose Vehicle Act.

Figure 3.1
Levels of Non-Performing Loans for the Period 1996-2005



Source: Bangko Sentral ng Pilipinas

By definition, NPLs account for the largest portion of classified accounts, hence the trend presented above also applies to the trend of classified accounts. For the nine banks under study classified accounts amount to an average of 31 and 20 percent of the total loan portfolio and total assets, respectively (without regard to time or period they are reported). Bank 8 recorded the lowest ratio of classified accounts to total loan portfolio while Bank 7, the highest. In terms of ratio of classified accounts to total assets, Bank 1 has the lowest with Bank 7 again having the highest. See Table 3.1 below.

Table 3.1
Ratio of Classified Accounts to Total Loan Portfolio and Total Assets: Various Reporting Periods

Bank ID	Reporting Date	Percent of Classified Accounts To Total Loan Portfolio	Percent of Classified Accounts To Total Assets
(1)	(2)	(3)	(4)
1	31-Mar-04	19.1	9.9
2	30-Jun-03	25.2	20.0
3	31-Dec-04	23.0	10.2
4	30-Jun-03	26.3	21.8
5	31-Mar-05	51.5	30.2
6	31-Jan-04	28.4	15.1
7	30-Sep-04	61.1	39.0
8	31-Dec-04	14.3	11.2
9	31-Mar-04	25.7	18.1

Tables 3.2 3.3, and 3.4 provide some numerical description of the data on outstanding balances of classified accounts, provision, and the estimated expected losses from each accounts using an LGD rate of 73 percent for the nine banks under study. The nine banks represent 42.5 percent of the total assets of the 41 commercial/universal banks in the Philippines as of 30 September 2005. The number of observations refer to the number of bank loans that were classified as of a given reference period. The reference period or the reporting period varies across banks since selection of data (or bank) depended on latest available ROE. The mean, median, minimum and maximum provides the description of the distribution of values of classified accounts and the provisions set aside to cover expected losses. Values of these statistics revealed the concentration of classified accounts to the smaller categories, and the presence of few very large loans. The value of the mean falls far right to the median and the median to the right of the mode, characteristic of a positively skewed distribution.

Annex 3 and 5 describe these distributions in graphical form. For the data on provision all banks exhibit concentration of observations in the below 100 million pesos. The highest concentration of values in this lowest category can be seen in Bank 3. Bank 8 on the other hand has the shortest range of values of provision ranging from 0.001 to about 117 million pesos with Bank 5 following next. This resulted to a closer to normal approximation of the simulated credit loss distribution. All other banks show very large outlying values resulting to skewed distributions of simulated data.

Table 3.2
Summary Statistics on Outstanding Balances of Classified Accounts (In million pesos): Various Reporting Periods

Bank	No. of Obs	Mean	Median	Mode	St. Dev.	Min	Max
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	1,247	26.254	2.706	0.500	198.127	0.003	6,664.384
2	585	44.454	1.046	0.500	157.242	0.006	2,288.237
3	1,069	14.476	0.250	0.005	105.871	0.001	2,578.308
4	271	57.247	10.000	10.000	221.353	0.001	3,003.447
5	141	53.079	3.408	0.250	113.618	0.010	451.216
6	1,975	20.631	1.750	0.250	88.766	0.002	1,545.000
7	416	74.201	9.579	0.003	222.401	0.001	2,778.003
8	421	14.367	1.600	0.340	40.373	0.007	393.524
9	279	26.682	2.714	0.000	93.496	*	943.370

* Less than P1,000

Table 3.3
Summary Statistics on Provision Made for Classified Accounts: Various Reporting Periods

Bank	No. of Obs	Mean PhP Mio	Median PhP Mio	Mode PhP Mio	St. Dev. PhP Mio	Min PhP Mio	Max PhP Mio
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	1,247	10.566	1.269	1.000	47.072	0.000	1,134.560
2	585	15.599	0.171	0.050	84.887	0.001	1,540.805
3	1,069	4.816	0.060	0.005	42.036	0.001	1,088.910
4	271	13.978	1.800	1.000	54.618	0.050	721.049
5	141	11.199	1.700	0.200	27.931	0.002	200.000
6	1,975	8.271	0.516	0.250	36.250	0.003	772.500
7	416	25.352	1.320	1.000	128.050	0.014	1,801.786
8	421	4.605	0.497	0.045	11.036	0.001	116.644
9	279	11.477	0.580	*	63.200	*	943.370

* Less than P1,000

Table 3.4
Summary Statistics on Expected Losses from Defaulted Accounts : Various Reporting Periods

Bank	No. of Obs	Mean PhP Mio	Median PhP Mio	Mode PhP Mio	St. Dev. PhP Mio	Min PhP Mio	Max PhP Mio
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	1165	18.509	1.862	0.730	148.611	0.002	4865.000
2	491	32.692	0.718	0.365	121.493	0.004	1670.413
3	971	9.251	0.121	0.000	74.782	0.001	1882.165
4	227	40.404	7.093	7.300	166.382	0.001	2192.516
5	127	32.623	2.000	multimodal	75.533	0.007	328.500
6	1758	14.480	1.102	0.183	63.150	0.001	1127.850
7	320	53.077	6.279	bimodal	170.501	0.001	2027.942
8	355	9.950	1.059	multimodal	28.160	0.005	287.273
9	232	19.813	1.630	0.000	72.387	0.000	688.660

* Less than P1,000

Annex 4 and 6 provide a graphical description of the distribution of the simulated loss data using provision and LGD rate, respectively. All banks exhibit fatter than normal tails and longer right tail of the distribution. Goodness of normal fit yielded negative results at .01 level of confidence. Thus VaR estimates using gamma approximations were computed. Estimation of the alpha parameter of the gamma distribution yielded values more than 6 which means that the distribution is approximately symmetrical and a normal approximation may be used.

Tables 3.5 and 3.6 provide comparative estimates of VaR using Approach 1 and Approach 2, respectively. Estimates are expressed as a percentage to total loan portfolio. Slight deviations from the bootstrapped estimates can be observed with few exceptions for banks with more pronounced skewness in which differences become larger at 0.01 confidence level. Using both approaches, the bootstrapped estimates are larger than the gamma approximations at five percent confidence level. The reverse is true at 0.01 level of confidence.

Table 3.5
Comparative Estimates of Value-at-Risk
cent to Total Loan Portfolio Net of Specific Provision, Approach 1)

ank	95%		99%		99.9%	
	Boot	Gamma	Boot	Gamma	Boot	Gamma
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	10.39	10.13	11.03	10.96	11.77	11.94
2	7.90	7.65	11.37	11.48	12.52	13.25
3	30.55	29.61	22.25	22.74	24.77	26.79
4	11.75	11.37	11.95	12.10	13.20	14.03
5	17.23	16.99	18.81	18.96	20.65	22.01
6	15.64	15.22	16.31	16.18	17.22	17.25
7	39.14	37.12	43.14	43.74	47.78	50.20
8	5.89	5.70	6.23	6.18	6.63	6.65
9	20.41	19.36	22.92	23.28	25.84	28.38

Table 3.6
Comparative Estimates of Value-at-Risk
(% to Total Loan Portfolio Net of Specific Provision, Approach 2)

Bank	95%		99%		99.90%	
	Boot	Gamma	Boot	Gamma	Boot	Gamma
(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	19.92	19.30	21.88	22.16	24.17	25.69
2	16.84	16.36	18.14	18.12	19.66	20.25
3	34.70	33.61	38.37	39.11	42.64	45.92
4	27.66	26.80	30.69	31.39	34.21	37.09
5	44.90	43.54	48.95	49.26	53.65	56.22
6	24.38	23.84	25.68	25.47	27.18	27.39
7	57.50	55.82	62.21	62.30	67.68	70.11
8	11.31	11.00	12.11	12.07	13.05	13.36
9	26.12	25.31	28.72	29.12	31.75	33.80

Table 3.7 below gives the bootstrapped values of capital for unexpected losses using both approaches expressed as a percentage to total loan portfolio (net of specific provision). Likewise, regulatory capital is expressed in percent to total loan portfolio. Note that these figures are snap-shot figures as these are simulated using data on a given reporting period. Historical data can not be established due to changes in the definition of those falling within categories and provision rates, thus results should not be interpreted as average values over different time horizons. Due to unavailability of estimates of regulatory capital for two banks (either the report is not yet final or the regulatory capital can not be derived from the available records as of the time of writing) comparison is limited to seven banks.

Results show that except for Bank 7, Approach 1 seems to underestimate the unexpected losses for the entire loan portfolio. This is due to the presence of specially mentioned accounts for which provision is very small (only 5 percent). On average however, LGD rate estimated from the provision rates for the original data set ranges from 45-60 percent for the nine banks under study. Clearly, provision underestimates losses since the realized LGD rate is actually 73 percent. The very large proportion of classified accounts (61.1 percent) to total loan portfolio of Bank 7 explains the high estimated value of its unexpected loss using Approach 1 meaning the sample is a good representation of expected losses for the bank, howbeit this still is an underestimation due to the reason stated earlier.

Using the realized losses from the sale of NPAs (Approach 2) however, it seems that the current risk-based capital assessment is underestimating loan losses. More specifically for banks with large number of defaulting loans and with high proportion of defaulted loans to total loan portfolio like Bank 7, the estimated loss is far more than the regulatory capital. High values of estimated UL are observed among banks with wider range of values of expected losses like Banks 3, 4 and 7 (see Table 3.4). Although Bank 1 has the widest range of values of losses, the expected losses are mostly concentrated in the below 100 million pesos.

Table 3.7
Comparative Table of Unexpected Losses Expressed as Percentage of Total Loan Portfolio Net of Specific Provision

Bank	Regulatory Capital	95%		99%		99.9%	
		Using Provision	Using LGD Rate	Using Provision	Using LGD Rate	Using Provision	Using LGD Rate
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	8.57	2.04	11.58	2.69	13.54	3.43	15.83
2	8.82	3.16	9.62	4.16	10.93	5.31	12.44
3	8.76	6.91	21.52	9.08	25.20	11.59	29.47
4	9.76	3.43	20.22	4.51	23.25	5.76	26.76
6	10.16	2.51	11.27	3.30	12.56	4.21	14.07
7	11.00	12.74	31.11	16.74	35.82	21.39	41.29
9	7.36	8.00	13.70	10.51	16.31	13.43	19.34

If we take provision as covering for expected losses for classified accounts, then it would be interesting to compare the simulated unexpected loss to the capital that would be obtained for NPLs alone. Non-performing loans for housing purposes fully secured by first mortgage on residential property (NPL_H) are currently given risk weight of 75 percent while all other nonperforming loans (NPL_A) are given risk weight of 125 percent. NPLs not for housing purposes account for a large portion of the total NPL hence comparison can be made against the capital that would be obtained using risk weight of 125 percent. Table 3.8 below shows the estimated unexpected losses in proportion to the total classified accounts. At 0.1 percent confidence level, only one bank would meet its capital requirement for its unexpected losses due from classified accounts at 125 percent risk weight. At one percent and five percent, some banks would but majority would not. Banks with very few outlying values of classified accounts would have lower estimates of unexpected losses like Bank 5 and Bank 8.

Table 3.8
Comparative Measures of Capital for Unexpected Loss (Approach 1) Expressed as a Percentage of Classified Accounts

Bank	Capital for Unexpected Loss		
	(95.0%)	(99.0%)	(99.9%)
(1)	(2)	(3)	(4)
1	9.87	12.96	16.57
2	15.39	20.23	25.84
3	17.44	22.74	29.27
4	11.25	14.79	18.89
5	8.70	11.44	14.61
6	7.74	10.30	12.99
7	16.49	21.67	27.69
8	7.32	9.62	12.29
9	27.71	36.42	46.52

6. Summary, Conclusion and Recommendations

The simulation of credit loss distribution using the data on classified accounts is based on the assumption that provisions cover expected losses. Results show that using this data in simulating the credit loss distribution would yield estimates lower than the regulatory capital, except for cases when the classified accounts represent a large portion of the total loan portfolio.

Simulating on provision may however give an idea of the appropriateness of the risk weights attached to NPLs if the UL is expressed in percent of the total classified accounts. Results show that the proportion of unexpected losses to total classified accounts is higher than the risk-weights attached to NPLs, hence, a higher risk weight for classified accounts is being suggested. This is further supported by the results in Approach 2 in which the resulting percentages of unexpected losses are greater than the risk-based capital. This goes well with the plan in the Philippines, of increasing risk weight from 75 to 100 and 125 to 150 percent in 2007 for NPL_H and NPL_A, respectively.

It is recognized however that bootstrap estimation of the tail of the distribution may not work well with small samples such as those below 100 but will have excellent results at 99.0 percentile for sample size of 1,000 and above (see Efron and Tibshirani, 1993, Chernick, 1999).

It is also recognized that robust estimation for capital, requires data spanning at least one whole economic cycle and the use of the methodology for all types of banks. Thus, before making any policy recommendation there is a need to use the methodology for more banks and for several years of data to establish the trend.

Furthermore, there is also a need to gather a more complete data (covering not only the classified accounts but all accounts and data on annual losses) to facilitate comparison of the estimates using model-based methodologies as suggested by the more advanced approaches in measuring credit risk.

If the trend is established by historical data, an alternative to increasing risk weight is to increase provision rates for classified accounts.

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Annex 1

Guidelines for Classifying Non-Performing Loans

Non-performing loans are subject to specific provisions depending on several conditions including the number of days past due. The summation of provisions made at different credit classification categories may be equated to the overall expected loss. The BSP defines the categories according to the following guidelines:

Loans specially mentioned. These are loans and advances that have potential weaknesses that deserve management's close attention. These potential weaknesses, if left uncorrected, may affect the repayment of the loan and thus increase credit risk to the bank. Their basic characteristics are as follows:

a. Loans with unlocated collateral folders and documents including, but not limited to, title papers, mortgage instruments and promissory notes;
b. Loans to firms not supported by board resolutions authorizing the borrowings;
c. Loans without credit investigation report/s;
d. Loans with no latest income tax return and/or latest audited financial statements, except consumer and small and medium enterprises (SME) loans which are current, have not been restructured and are supported by latest income tax returns and/or latest audited financial statements at the time they were granted ;

For this purpose, consumer loans is defined to include housing loans not exceeding P5 million, loans for purchase of car, household appliance(s), furniture and fixtures, loans for payment of educational and hospital bills, salary loans and loans for personal consumption.

e. Loans the repayment of which may be endangered by economic or market conditions that in the future may affect the borrower's ability to meet scheduled repayments as evidenced by a declining trend in operations, illiquidity, or increasing leverage trend in the borrower's financial statements;
f. Loans to borrowers whose properties securing the loan (previously well secured by collaterals) have declined in value or with other adverse information;
g. Loans past due for more than thirty (30) days up to ninety (90) days; and
h. Loans previously cited as *Miscellaneous Exceptions* still uncorrected in the current BSP examination.

Miscellaneous exceptions – Loans. These are loans with technical defects, deficiencies in documentation/collaterals and without-up-to-date credit information/ audited financial statements/income tax returns. These exceptions should be brought to management's attention for corrective action during examination. This category may include the following:

i. Loans with unregistered mortgage instrument which is not in compliance with the loan approval;
ii. Loans with improperly executed supporting deed of assignment/pledge agreement/chattel mortgage/real estate mortgage;
iii. Loans with unnotarized mortgage instruments/agreementsiv. Collaterals not covered by appraisal reports or appraisal reports not updated;
v. Loan availment against expired credit line; availment in excess of credit line; availments against credit line without prior approval by appointing authority;
vi. Loans with collaterals not insured or with inadequate/expired insurance policies or the insurance policy is not endorsed in favor of the bank;
vii. Loans granted beyond the limits of approving authority;
viii. Loans granted without compliance with conditions set forth in the approval; and
ix. Loans secured by property the title to which bears an uncancelled annotation of lien or encumbrance

Substandard. These are loans and advances or portions thereof which appear to involve a substantial and unreasonable degree of risk to the institution because of unfavorable record or unsatisfactory characteristics. There is a possibility of future loss to the institution unless given closer supervision. Those classified as "substandard" must have a well defined weakness or weaknesses that jeopardize their liquidation. Such well-defined weaknesses may include adverse trends or development of financial, managerial, economic or political nature, or a significant weakness in collateral. No loans/advances should be classified "substandard" if repayments/collections seem reasonably assured. Their basic characteristics are as follows:

a. Secured loans
(1) Past due and circumstances are such that there is an imminent possibility of foreclosure or acquisition of the collateral because of failure of all collection efforts;

(2) Past due loans to borrowers whose properties securing the same have declined in value materially or have been found with defects as to ownership or other adverse information;
(3) Current loans to borrowers whose audited financial statements show impaired/negative net worth except for start-up firms which should be evaluated on a case-to-case basis.

Loans and advances possessing any of the above characteristics shall be classified "Substandard" at the full amount except portions thereof secured by hold-outs on deposits, deposit substitutes, margin deposits, or government-supported securities. The portions so secured are not subject to classification.

b. Unsecured loans
(1) Renewed/extended loans of borrowers with declining trend in operations, illiquidity, or increasing leverage trend in the borrower's financial statements without at least twenty percent (20%) repayment of the principal before renewal or extension; and
(2) Current loans to borrowers with unfavorable results of operations for two (2) consecutive years or with impaired/negative net worth except for start-up firms which should be evaluated on a case to case basis.

c. Loans under litigation
d. Loans past due for more than ninety (90) days;
e. Loans granted without requiring submission of the latest audited financial statements (AFS)/income tax returns and/or statements of assets and liabilities to determine paying capacity of the borrower;
f. Loans with unsigned promissory notes or signed by unauthorized officers of the borrowing firm; and
g. Loans classified as "Loans Especially Mentioned" in the last BSP examination which remain uncorrected in the current examination.

Doubtful. These are loans or portions thereof which have the weaknesses inherent in those classified as "Substandard", with the added characteristics that existing facts, conditions, and values make collection or liquidation in full highly improbable and in which substantial loss is probable. Their basic characteristics are as follows:

a. Past due clean loans and advances classified as "substandard" in the last BSP examination without at least twenty percent (20%) repayment of principal during the succeeding twelve (12) months or with current unfavorable credit information;

b. Past due loans and advances secured by collaterals which have declined in value materially such as inventories, receivables, equipment, and other chattels without the borrower offering additional collateral for the loans and previously classified "substandard" in the last BSP examination.;
c. Past due loans secured by real estate mortgage, the title to which is subject to an adverse claim rendering settlement of the loan through foreclosure doubtful; and
d. Loans wherein the possibility of loss is extremely high but because of certain important and reasonably specific pending factors that may work to the advantage and strengthening of the asset, its classification as an estimated loss is deferred until a more exact status is determined.

Loss. These are loans and advances or portions thereof which are considered uncollectible or worthless and of such little value that their continuance as bankable asset is not warranted although the loans may have some recovery or salvage value. The amount of loss is difficult to measure and it is not practical or desirable to defer writing off this basically worthless asset even though partial recovery may be obtained in the future. Their basic characteristics are as follows:

a. Past due clean loans and advances the interest of which is unpaid for a period of six (6) months;
b. Those payable in installments where amortization applicable to interest is past due for a period of six (6) months, unless well secured;
c. When the borrower's whereabouts is unknown, or he is insolvent, or his earning power is permanently impaired and his co-makers or guarantors are insolvent or that their guaranty is not financially supported;
d. Where the collaterals securing the loans are considered worthless;
e. Loans considered as absolutely uncollectible; and
f. Loans classified as "Doubtful" in the last BSP examination and without any payment of interest or substantial reduction of principals during the succeeding twelve (12) months, or have current unfavorable credit information which renders collection of the loans highly improbable.

Note that the value of the collateral is already accounted for in classifying the accounts such that the schedule of provisioning below can be assumed as the estimated expected loss for each classified account.

Category	**Provision** (percent of outstanding balance)
Loans especially mentioned	
by 12.31.98	2.5
by 4.15.99	5.0
by 12.31.02	5.0
Substandard – secured	
by 12.31.98	12.5
by 4.15.99	25.0
by 12.31.02	10.0
Substandard – unsecured	25.0
Doubtful	50.0
Loss	100.0

Annex 2

Technical Notes on Bootstrap and STATA

The bootstrap is a computer-intensive method developed by Bradley Efron (1979) and others to derive standard errors of estimates from information in the sample and do statistical inference. It is a type of Monte Carlo method applied based on observed data.

The most fundamental idea of the bootstrap method is the estimation of inference uncertainty from the estimated sampling distribution of the conceptual probability distribution *f*. In practical application, the bootstrap means using some form of re-sampling with replacement from the actual data, *x*, to generate B bootstrap samples, $\underline{x^*}$. Often the data (sample) consist of *n* independent units and it then suffices to take a simple random sample of size *n*, with replacement, from the *n* units of data, to get one bootstrap sample. However, the nature of the correct bootstrap data re-sampling can be more complex for more complex data structures.

The set of B bootstrap samples is a proxy for a set of B independent real samples from *f*. Properties expected from replicate real samples are inferred from the bootstrap samples by analyzing each bootstrap sample exactly as the real data sample is analyzed. From the set of results of sample size *B,* the inference uncertainties from sample to conceptual population are measured. The bootstrap can work well for large sample size (n), but may not be reliable for small n (say 5, 10, or even 20), regardless of how many bootstrap samples, *B*, are used (Efron, 1993).

The logic behind the bootstrap is this: All measures of precision come from a statistics' sampling distribution. The sampling distribution gives the relative frequencies of the values of the statistic when the statistic is estimated on a sample of size n from some population. The sampling distribution in turn, is determined by the distribution of the population and the formula used to estimate the statistic.

In some cases, the sampling distribution can be derived analytically. For instance, if the underlying population is distributed normally, and one calculates the means, the sampling distribution for the mean is distributed as t with n-1 degrees of freedom. In other cases, deriving the sampling distribution is too hard, as in the case of means calculated from non-normal populations. Sometimes, as in the case of means, it is not too difficult to derive the sampling distribution as $n \rightarrow \alpha$. The distribution of means converges to a normal. The asymptotic result is then used to calculate some measure of statistical precision on a finite sample of size n even though it is incorrect.

Mechanically, the procedure is this: One has a dataset containing n observations and an estimator which, when applied to the data, produces certain statistics. One draws, with replacement, n observations from the n observation dataset. In this random drawing, some of the original observations will appear once, some more than once, and some, not at all. Using the dataset, one applies the estimator and estimates the statistics. One does it again, drawing a new random sample and re-estimating, and again, and keeps track of the estimated statistics at each step of the way (called a replication).

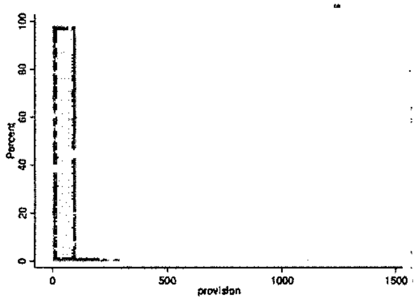
Technical Description of STATA

STATA like SAS and SPSS, is a general purpose statistical software package. It is command-based software, available for Windows, Mac, OS, and UNIX systems. STATA provides high flexibility in the interactive mode, which makes it easier for beginners to learn and use. For example, STATA can run ordinary least squares (OLS) or draw a graph with a single command. Furthermore, STATA programming features make it easy to conduct maximum likelihood estimation and matrix manipulation.

STATA provides a broad range of analyses, including regression model, analysis of variance (ANOVA), limited dependent models (e.g. logit, probit), panel data analyses, survival analysis, cluster analysis, multivariate methods, non-parametric methods and time series analysis.

Distribution of Provision for Classified Accounts

Bank 1



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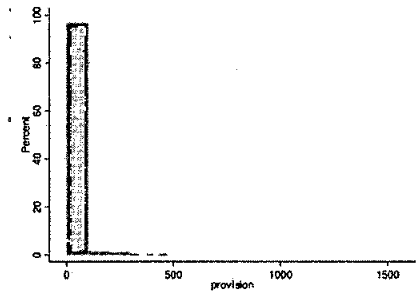

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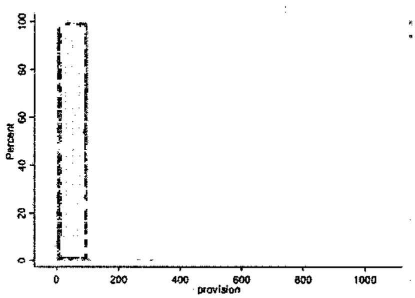

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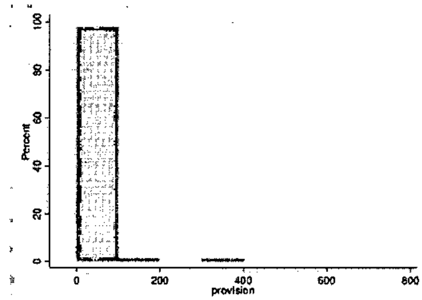

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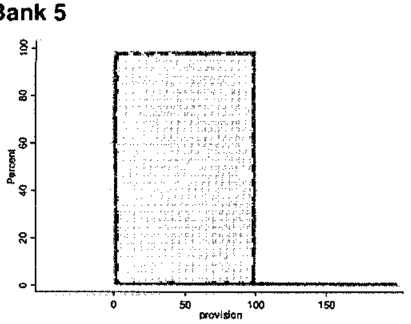

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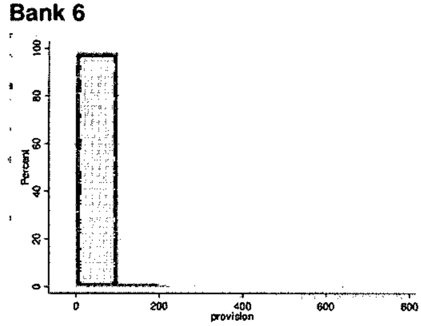

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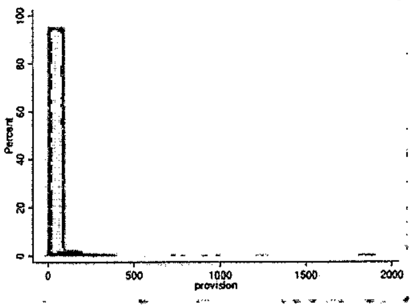

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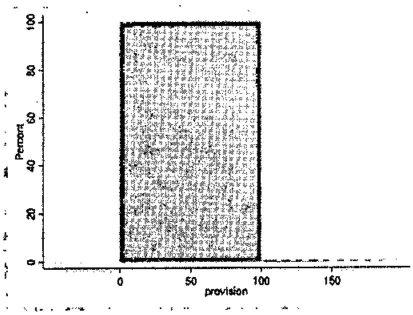

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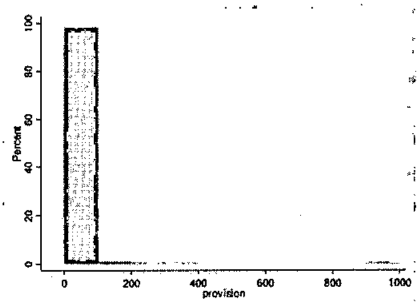

Distribution of Simulated Loss Data, Using Provision

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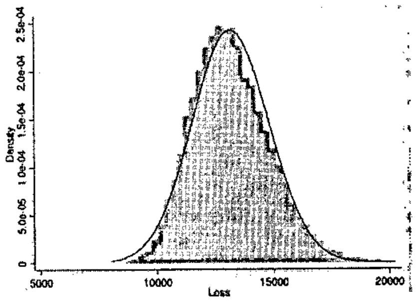

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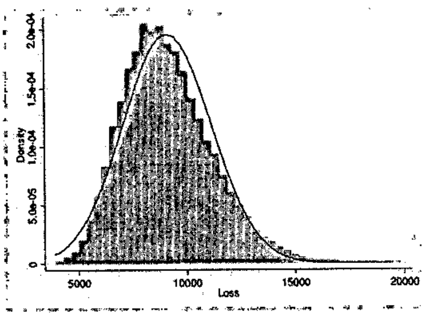

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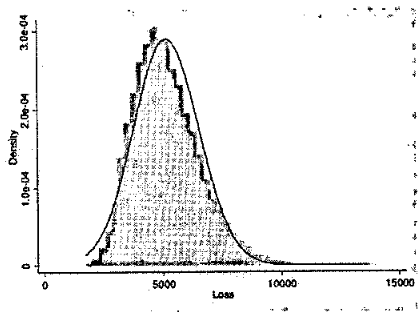

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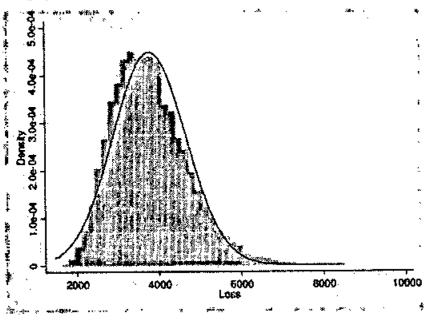

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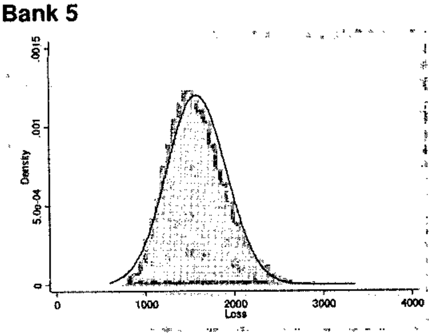

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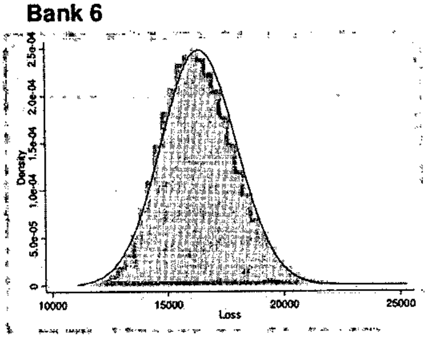

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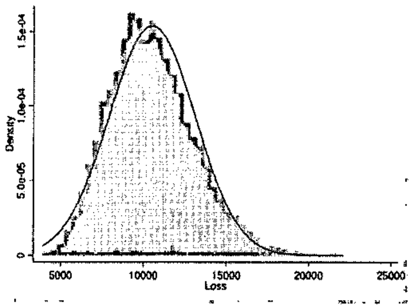

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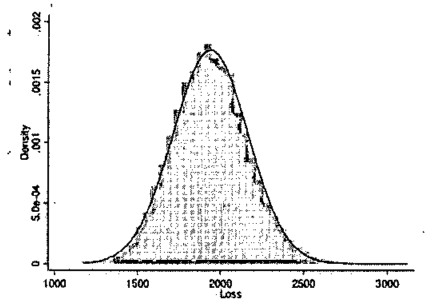

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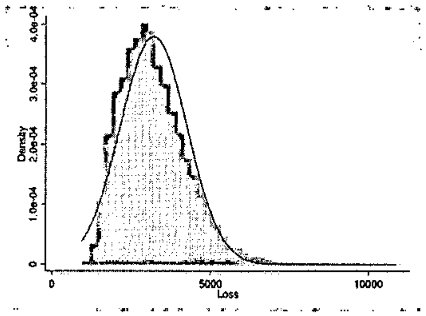

Distribution of Loan Losses Using Realized LGD

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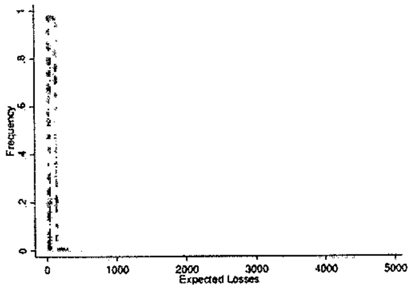

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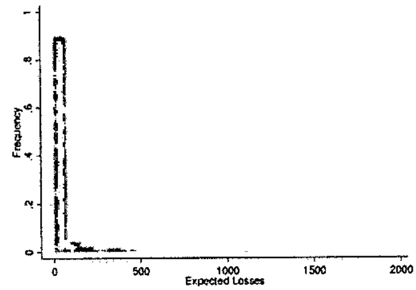

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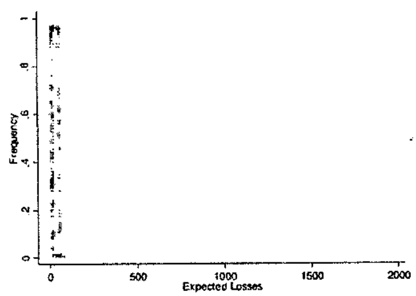

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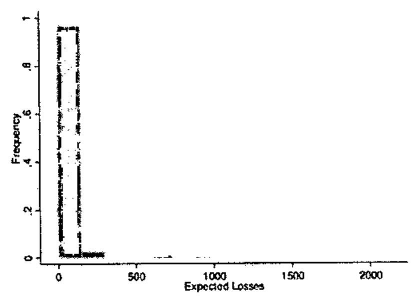

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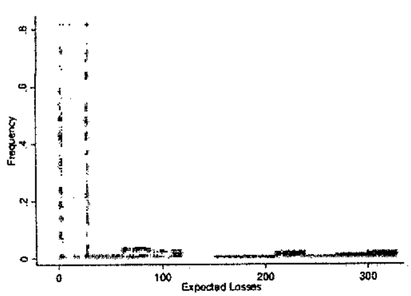

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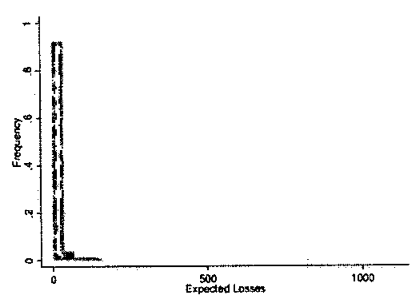

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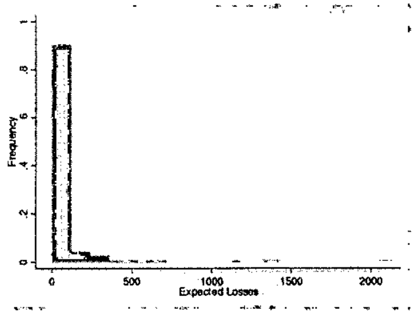

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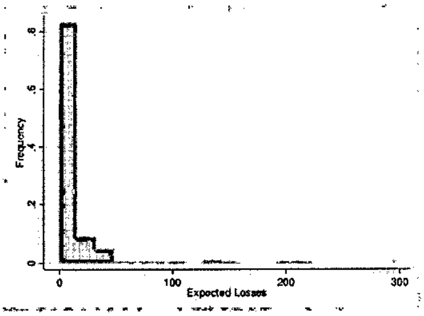

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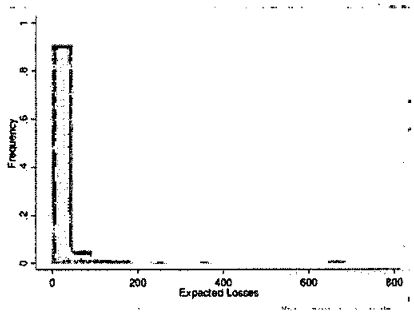
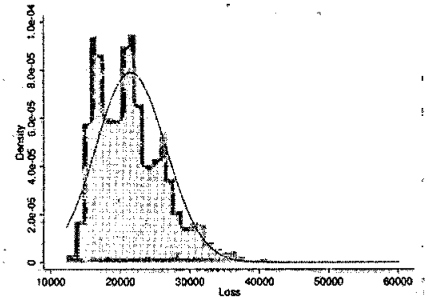


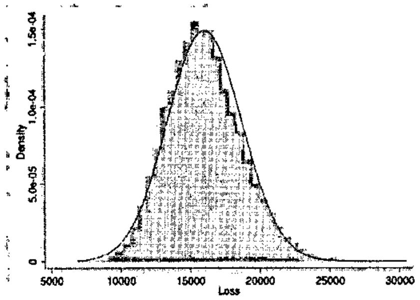
Annex 6

Distribution of Simulated Loss Data, Using LGD Rate of 73%

Bank 1



Bank 2



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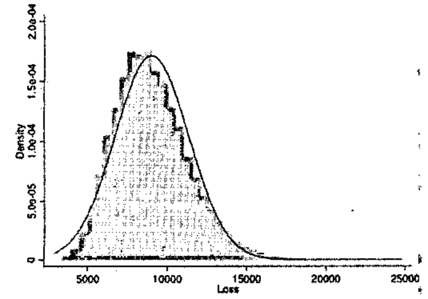

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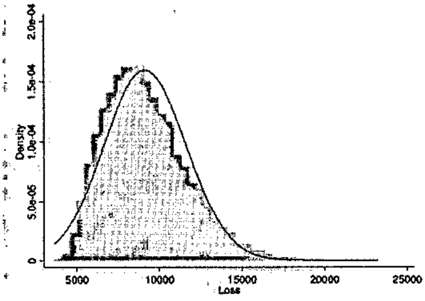

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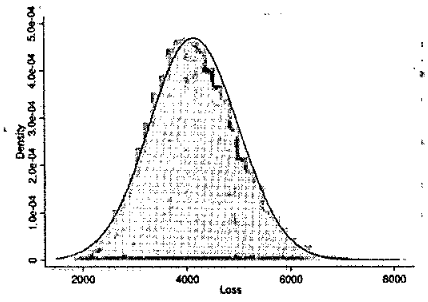

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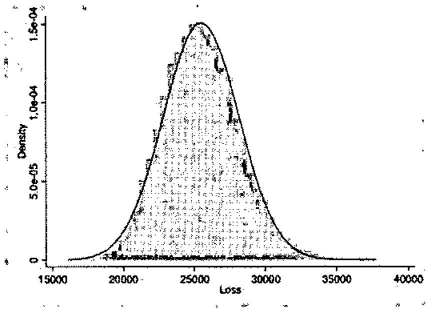

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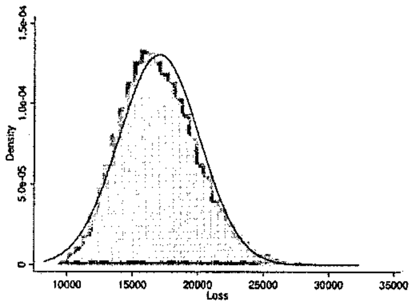

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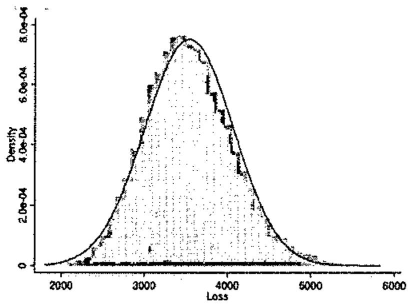
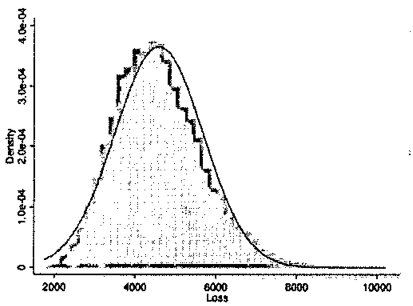


Bank 9



CHAPTER 4

ADEQUACY OF THE EXISTING LEVELS OF CAPITAL IMPLIED BY THE BASEL STANDARDS, RELATIVE THE CREDIT EXPOSURES OF BANKS IN SRI LANKA

by
V. Sivanesan[6]

1. Introduction

The Central Bank of Sri Lanka (CBSL), compatible with its goal to have consistency and harmony with international standards and its approach to adapt to a pace that is appropriate in the context of country specific needs, has decided to adopt the new capital accord with effect from January 2008. All banks in Sri Lanka, to begin with, will adopt the Standardized Approach for credit risk and the Basic Indicator approach for operational risk. A parallel run of Basel II along with Basel I has commenced from the first quarter of 2006. CBSL may consider allowing some banks to migrate to Internal Rating Based (IRB) approaches after developing adequate processes and skills both in banks and at supervisory levels.

The Standardized approach for credit risk is modeled on the existing risk-weighting methodology of Basel I. However, unlike Basel I, the risk-weightings under Basel II are more granular and are broken down according to external credit ratings. Sri Lanka, however like many emerging economies, has only two rating agencies and the level of rating penetration is very low. At present only few exposures of banks are rated. Under the standardized approach, the unrated assets of Banks will be risk weighted at 100 percent. Most of the assets of banks in Sri Lanka will be risk weighted at 100 percent. This would mean the capital measurement will basically remain at Basel I and there wouldn't be much gain in terms of risk sensitivity, a key objective of Basel II. The limited number of rated claims in the emerging economies will effectively render the standardized approach less effective. The Rating agencies mainly rate large entities whereas Banks in the emerging economies grant loans to large number of small players and most of the loans of banks in our region have not been rated. In such a scenario the basic approaches to which Sri Lanka has decided to move to will be similar to Basel I, with few exceptions such as the introduction of a lower regulatory capital for the retail portfolio, high capital charge for the NPAs with

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low provision cover. As a result, the level of capital implied by the Basel II may not be reflective of the level of credit risk.

With a view to assessing the adequacy of the capital level in the Sri Lanka banking system, on a sample basis, this paper investigates whether the existing levels of capital in the Sri Lankan banking system is adequate given the credit risk exposure of banks. To do this first the credit risk of the banking system needs to be estimated. This is generally done by the use of credit risk models. However, in the absence of sophisticated credit risk measurement methodologies, this paper proposes a simplified methodology almost similar to the one adopted by Majnoni et al in their study entitled 'Bank Capital and Loan Loss Reserves under Basel II: Implications for Emerging countries' (October, 2004), for measuring credit risk using information extracted during the on site examinations of banks and/or from the statements submitted by banks to the CBSL.

The credit risk measure from this model is an Expected Loss (EL) figure, which is then used to derive a level of capital adequate to cover a specified level of risk, using the value-at-risk approach. Value at risk is considered as the total of Expected Loss and Unexpected Loss (UL). The resulting capital level is then compared with the capital level under the existing risk-based capital adequacy framework, to determine whether the existing capital level is adequate to cover the credit risk exposure of banks in the sample. The focus of this research is only on credit risk.

Bootstrapping, a re-sampling technique is used with a view to replicating the distribution of credit losses prevailing in each bank. The bootstrap is a computer-intensive method developed by Bradley Efron and others to derive standard errors of estimates in the sample and do statistical inference. This technique was adopted by Majnoni (2004) in estimating bank capital and in setting loan loss reserve regulation. To minimize the impact of errors on the estimation of the credit loss distribution function and to maximize the degree of comparability across banks, bootstrapping enables to mimic the shape of the loss distribution function of any specific loan portfolio. Notwithstanding the lack of an underlying model, bootstrapping techniques can be used to simulate the impact that specific shocks or cyclical impulses have on the frequency distribution of credit losses. The great advantage of bootstrap is that it makes it reasonably easy to produce comparable statistics across banks. This technique allows replicating the real risks faced by banks without specific knowledge or assumptions regarding the factorial structure of risk or the correlation among different risk factors. The lack of an underlying model does not prevent from quantifying the amount of capital and provisions that are necessary to shelter a bank from the risk of default at any level of probability.

2. Sri Lankan Banking System

The Banking industry in Sri Lanka consist of commercial banks (23 LCBs) and specialized banks(14 LSBs), the distinguishing feature between the two being, the former accept demand deposits and operate current accounts and thus become part of the payment and settlements system and are authorized dealers in foreign exchange. The latter do not engage in any of these operations – they undertake specialized banking activities and take the form of savings banks, housing banks, rural banks and development finance banks.

LCBs dominate the Sri Lankan Banking System with 81 percent of the total banking sector assets. The systemic importance of the LSB sector is relatively low when compared with the LCB sector, both in terms of their size and their impact on the financial system. The 14 LSBs in operation accounted for 19 percent of the total banking sector assets. This study focuses only on the commercial banking sector and the LCB sector comprised of two state banks, nine domestic private commercial banks and twelve foreign banks. The greatest risk faced by banks in Sri Lanka is the credit risk, as loans form a dominant share of the asset portfolio of banks. The NPL ratio of LCBs stood at seven per cent as at end-December 2005. The key indicators of commercial banking industry are given in Table 4.1.

Table 4.1
Key Indicators of Commercial Banks (As at Dec 2005)

Capital Adequacy Ratio – Tier I (%)	11.5
Capital Adequacy Ratio – Total (%)	12.4
Gross NPA %	7.0
Net NPA %	2.1
Provision Coverage (loan loss provision/ loans)	70.0

2.1 Definition of Default and Provisioning Requirements

CBSL, the supervisory authority in Sri Lanka, defines Non-Performing Advances/Loans (NPA/L) as the advances wherein the capital and/or interest are in arrears for a period of three months or more. Overdraft accounts that have been static and are in excess of the approved limit for three months or more are classified as NPA.

The Basel Committee on Banking Supervision (BCBS), International Convergence of Capital Measurement and Capital Standards: A Revised Framework (Basel II) specifies a reference definition of default to be used for recording defaults and estimating probability of default, loss given default and exposure at default when using the internal ratings-based (IRB) approach. It states that default occurs when (1) the bank considers that an obligor is *unlikely to pay* its credit obligations to the bank in full, without recourse by the bank to actions such as realizing security or (2) the borrower is past due for more than 90 days on any material credit obligation to the bank.

Unlikely to pay is evidenced by (1) *The bank puts the credit obligation on non-accrued status*; (2) th*e bank makes a charge-off or account-specific provision resulting from a significant perceived decline in credit quality subsequent to the bank taking on the exposure*; (3) the bank sells the credit obligation at a material credit-related economic loss;(4) t*he bank consents to a distressed restructuring of the credit obligation where this is likely to result in a diminished financial obligation caused by the material forgiveness, or postponement, of principal, interest or (where relevant) fees*; (5) the bank has filed for the obligor's bankruptcy or a similar order in respect of the borrower's credit obligation to the bank; and (6) the borrower has sought or has been placed in bankruptcy or similar protection where this would avoid or delay repayment of the credit obligation to the bank.

Although the number of days (90 days) past due is aligned under CBSL definition of NPA and Basel II definition of default, the other criteria for a default occurrence as indicated in the Basel II definition are not taken into account in the existing CBSL definition of NPAs. CBSL does not allow accrual of interest income for loans classified as non-performing. Banks are required to make provisions according to the status of classification of the NPAs. NPAs are classified under different categories, namely Substandard, Doubtful and Loss, depending on the situation of the borrower and default history. The criteria for the determination of the category of NPA accounts are at Annex 1. In addition to the specific provision banks are encouraged to maintain a general provision as a prudential measure. The banks make loan loss provisions on the net exposure (net of collateral value). Currently, the provision levels are satisfactory as indicated in the provision cover ratio of 70 percent. The valuation criteria of securities for provisioning purposes are given in Annex 2.

At present the risk based capital is determined by taking into account the credit and market risks of banks' exposures. In the computation of the capital requirement for credit risk, all on balance sheet and off balance sheet items are risk weighted in line with the Basel Capital Accord (Basel I). The performing and non performing loans are treated alike and risk weighted at 100 percent. For capital adequacy computation, risk weight is attached to advances net of specific provisions and interest in suspense.

3. Methodology and Data

The usual bootstrap procedure draws sample from the entire population the size of which is much smaller than the population size. This is specifically true for estimating the mean. Since the concern is the estimation of the tail of the distribution, it is necessary to produce a large number of replicates such that for this study, 20,000 replicates are deemed appropriate. From the simulated distribution, parameters such as the mean loss are estimated and the maximum amount of losses that can be experienced from bank's advance portfolio at different confidence levels at a particular point in time is computed, using the value at risk concept.

The major steps of the bootstrapping procedure are as follows:

a. Extract a random sample of 500 loans, intended to mimic the loan portfolio of each of the three banks, namely A, B and C. These are three large banks in Sri Lanka and their aggregate asset base account for 47 percent of the total commercial banking sector. In each bank's case the outstanding of each of these 500 customers were taken into consideration. Key financial indicators of banks included in the Sample are given in **Annex 3**.

Table 4.2
Characteristics of Chosen Samples

Banks	% PA in the Sample Portfolio	% NPA in the Sample Portfolio	% NPA of the Entire Bank	Total Sample – Advances Rs. Mn)	Sample as a % of Total Advances
A	85.4	14.6	11.1	78,740	42.8
B	92.4	7.6	5.9	21,392	17.2
C	87.3	12.3	9.0	33,258	29.0

PA- Performing Advances, NPA – Non-Performing Advances

b. This sample consists of both performing and non performing advances. Particular attention was paid in selecting a representative sample from each bank covering large exposures as well as certain small loans.

c. Given a predefined recovery ratio (assumed to be equal to 50 percent of the face value of a defaulted loan (NPA)) the value of the losses of the sampled portfolio is computed, expressing this as a fraction of the face value of the total outstanding advances.

d. The last step is replicated a large number of times (20,000 in our case) to generate a frequency distribution of credit losses that mimics the one faced by banks.

4. Data Limitations

Data limitations have not allowed sampling over several years and therefore the simulation results reported in this report should be interpreted as reflecting a photograph or snap-shot of a particular bank in a particular date. The results cannot and should not be interpreted as average values representing credit risk exposure over different time horizons, nor over the full economic cycle. While a robust parameterization for capital and loan loss reserves requires data spanning at least a whole cycle the evidence that we present here support the need of a careful calibration effort and for a new regulatory approach to capital and loan loss reserves in emerging economies.

5. Results

Tables 4.2 and 4.3 give the descriptive statistics of the distribution of randomly sampled loan portfolios and provisions. The concentration of loan-dimension toward the smallest size category is more evident in Bank B and C and show considerably more skewed distributions for both portfolio values and credit losses than the comparable distribution computed. The concentration of loan-dimension toward the smallest size category is more evident in bank B (50 percent of all the loans extracted are smaller than SLR 3.2mn) and in bank C (50 percent of all the loans extracted are smaller than SLR 3.0mn). In bank A, 50 percent of all the loans extracted are higher than SLR 29mn.

Table 4.3
Loans, Descriptive Statistics

Bank	No.Obs.	Mean LKR Mn	Median LKR Mn	SD LKR Mn	Min LKR	Max LKR Mn
A	500	157.0	29.0	454	13,749	7,320
B	500	42.8	3.2	138	4,555	1,740
C	500	66.5	3.0	287	200,000	2,930
Industry	1,500	88.9	7.4	324	4,555	7,320

Table 4.4
Provisions Made, Descriptive Statistics

Bank	No.Obs.	Mean LKR Mn	Median LKR Mn	SD LKR Mn	Min LKR	Max LKR Mn
A	500	11.5	0	37.8	0	346
B	500	1.6	0	8.5	0	108
C	500	4.0	0	17.8	0	236
Industry	1500	6.6	0	42.0	0	346

Expected Loss (EL) is the mean value (Observed Value) of the simulated distribution of credit losses. Simulations are based on the random sample of 500 loans obtained during the recent on site examinations and from the regular reports submitted to the CBSL, during the period between September-December 2005. The sample is repeated 20,000 times (with replacement) as per the bootstrap methodology to obtain 20,000 portfolios. The distribution of credit losses for each bank's portfolio provides the 20,000 observations used to simulate the distribution of credit losses. The industry figures were based on the aggregate portfolio (1,500 observations) of 3 banks in the sample.

Table 4.4 gives results of bootstrapping. The Unexpected Losses (UL) at different levels of probability (95 percent, 99 percent and 99.9 percent) represent the value of credit losses corresponding to the upper confidence limit on the right tail of the distribution minus the EL. Capital Adequacy Ratio (CAR) of banks are as at 12 December 2005. However, this CAR covers the entire asset base of banks. Column 7 of table 4.4 shows the percentage between the aggregate of risk weighted capital and loan loss provisions and the total loans. Column 9 shows difference between the total of EL and UL (at 99 percent confidence level) and column 7. The provision coverage of each bank is also given for comparison as the general assumption is that the expected loss should be covered by provisions.

For each bank the value of expected losses (EL) and the value of unexpected losses (UL) associated to each percentile level of the (right tail) simulated distribution of credit losses is given. Here the value-at-risk is the sum of expected and unexpected losses. The value at risk and its components, the expected and unexpected loss, are critical in defining the level of bank capital and loan loss reserves necessary to achieve a predefined level of protection (99 percent) of the banking system. Simulation results provide a measure of the size of expected losses and unexpected losses and of the values that capital and loan loss reserves need to achieve to protect banks from insolvency in 95 percent, 99 percent or 99.9 percent of negative occurrences ≤ or 95 percent, 99 percent and 99.9 percent of the distribution.

For the three banks considered, expected losses were in the range of 10.8 percent to 17.3 percent. The unexpected losses at 99 percent were in the range of 2.3 percent to 2.8 percent. For the banking industry as a whole, the expected loss level is 13.4 percent and the unexpected loss at 99 percent confidence level is 1.4 percent. The simulation indicates that the unexpected loss level in banks is considerably lower than the expected loss levels. The lower UL value in relation to the CAR could have been a result of the following:

1. As explained in paragraph 3 of this report the recovery ratio is assumed to be equal to 50 percent of the face value of a defaulted loan (NPA). The value of the losses of the sampled portfolio is computed as a fraction of the face value of the total advances. Thus, the risk of loss of the performing advances is not accounted for in the UL. However, the computation of Capital Adequacy Ratio includes both performing and non performing advances. This may have resulted in low UL compared to the Capital Adequacy Ratio.

2. While the Capital Adequacy Ratio captures other sources of credit risk in the banks such as investments and other assets, the UL value has been derived based only on the loan portfolio of banks. The UL value therefore is an underestimate.

Despite the results, it is deemed that the underlying need for the system is to attempt to gauge the overall value at risk of loans rather than their expected or unexpected loss components. Indeed it is the sum of provisions and capital that should be compared against the value at risk (the sum of expected and unexpected loss) and not necessarily provisions against expected loss and capital against the unexpected component. In Sri Lanka banks are permitted to consider securities such as immovable properties when making loan loss provisions ie: provisions are made on the net exposure (ie: net of collateral), therefore, the provision level would obviously not be sufficient to cover expected loss entirely. In other words, a portion of expected loss needs to be covered by capital, given the subjectivity in provisioning.

Further, if for some reason (legal or otherwise) there are impediments to increase capital to cover unexpected losses relative to the desired level of protection, then provisions might be increased over and above the level of expected loss. When we compare the results with the level of capital adequacy of all three banks individually and also with the industry figure, the total of expected and unexpected losses exceed the aggregate of risk based capital and loan loss provisions of the individual banks and also of the industry.

Inconsideration of the data limitations stated above, comparison was also made between VaR and the risk-based capital expressed as a proportion to total loan portfolio. Of the three banks analyzed, Bank C's total of expected and unexpected losses was much higher than the capital and provisions with a gap of 5.5 percent. In case of Bank B this gap is 4.2 percent. Of the three banks, Bank A is with reasonably good level of capital and provisions and has a gap of only 2.9 percent. Overall, it seems that the Sri Lankan banking industry needs more capital and provision cover.

Table 4.5
Credit Losses: Simulated Results

Banks	EL	UL 95%	UL 99%	UL 99.9%	CAR	Risk-Based Capital +Provision as % of Loans	VaR	Gap in %	Provision Cover
A	11.7	1.8	2.4	3.1	13.2	11.2	14.1	2.9	82.5
B	10.8	1.7	2.3	3.0	12.0	8.9	13.1	4.2	56.4
C	17.3	2.1	2.8	3.5	11.5	14.6	20.1	5.5	65.8
Industry	13.4	1.1	1.4	1.8	12.4	11.4	14.8	3.4	70.0

6. Policy implications

The total of expected and unexpected losses should serve as benchmark in assessing the sufficiency of economic capital set aside by bank for credit risk. The simulations were based on only the loan portfolio, excluding other risk assets. Thus, the results should be interpreted with caution as the capital adequacy ratio is on account of several other assets such as investments that are not taken into consideration in this study. In addition, banks are expected to hold capital to guard against other forms of risks such as market risk, liquidity risk and concentration risk that are not accounted for in the capital adequacy ratio. (The market risk component of the capital accord was introduced in Sri Lanka only from 31st March 2006).

In the simulations 'default' is defined as more than 90 days past due and the 'loss given default' is assumed to be 50 percent of the outstanding of non performing advances. The estimation of required levels of capital was based on the assumption that the loan loss provisions cover the expected loss. In fact in case of certain banks, provisions may cover more than expected loss and vice versa. As the provisions are made on the exposure, net of securities, the provision level may not be indicative of the actual level of expected losses.

Though this study included both performing and non performing advances, the simulations were only of the loan losses arising from the non performing portfolio, it should be appreciated that even in the performing loan portfolio there is a great potential for credit risk. To this extent, the estimates of losses in this study are understated. Therefore, the capital level needs to be higher than the level indicated in this study to cover the potential losses that might arise from the 'performing advances' portfolio. The existing capital adequacy framework treats both performing and non performing portfolios alike. However, the non performing portfolio has much higher probability of losses. The regulators, therefore, should formulate policies to improve their regulations with a view to capturing this 'high risk potential'. The provisioning policies also need to be strengthened, especially with regard to the eligible collaterals and the application of 'arbitrary' provision rates of 20 percent, 50 percent etc. and should be more forward looking.

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Annex 1

CLASSIFICATION OF ADVANCES AND LOAN LOSS PROVISIONS

The Central Bank of Sri Lanka (CBSL) requires banks to classify the Non Performing accounts under different categories, namely Substandard, Doubtful and Loss, depending on the situation of the borrower and default history. The specific criterion is as follows:

Substandard Account

Credit facilities of which the situation of the borrower makes it uncertain that part or the entirety of the facility will be repaid including those that are in arrears for six months or more but less than twelve months, shall be classified substandard. Characteristically, these are advances which involve more than normal risk of loss due to unsatisfactory debt servicing record or financial condition of the borrower, insufficiency of collateral or any other factors which give rise to some doubts as to the ability of the borrower to comply with the present repayment terms. Consequently there is also the distinct possibility that the bank will likely to sustain some loss if these deficiencies are not corrected. The banks are required to make a specific provision to cover the amount of the expected exposure, but not less than 20 percent of the amount of outstanding, net of any realizable security value and interest suspensed in the event such interest being debited to the advances account.

Doubtful Account

Credit facilities with a high risk of partial default including those that are in arrears for 12 to 18 months shall be classified doubtful. Usually these advances are accounts where full collection is improbable and there is a high risk of default. The banks are required to make a specific provision to cover the amount of the expected exposure, but not less than 50 percent of the amount outstanding, net of realizable value of security and interest suspensed in the event such interest being debited to the advances account.

Loss Account

Credit facilities where the situation of the borrower makes it virtually certain that the facility will not be repaid including those that are in arrears for over 18 months shall be classified loss. These advances are deemed uncollectible and worthless. The accounts classified loss should be covered by a specific provision equivalent to 100 percent of the amount of outstanding net of realizable security value, if any, and interest suspensed in the event such interest being debited to the advances account. Any bank that maintains a general provision to specific provisions calculated on the above basis is encouraged to do so as a more prudential measure.

VALUATION OF SECURITIES FOR PROVISIONING PURPOSES

(1) Primary Mortgage over Property

(*i*) At the time of first provisioning for a loan, only 75percent of the forced sale value (FSV) of the property based on a current professional valuation report can be considered as the value of security (*i.e.* an initial haircut of 25percent will be applied);

(*ii*) When an advance is transferred to the 'Loss' category, the following progressive discounts will apply to the forced sale value of immovable property held as collateral, based on a current professional valuation report, depending on the time period for which it remains in the 'Loss' category:
No. of years in loss category percent of FSV of immovable property that can be counted as the value of security

1-2 years -60%
2-3 years -50%
3-4 years -40%

All immovable property held as collateral, relating to loans in the Loss category for more than 4 years should be reviewed on a regular basis, and discounted further at the discretion of the Management.

Note: A 'Current professional valuation report',

i. In respect of loans granted against residential property which is occupied by the borrower for residential purposes is a report that is not more than four years old.

ii. In respect of loans granted for all other purposes is a report that is not more than three years old.

(2) Deposit of Title Deeds with an Undertaking to Mortgage

No value should be assigned until a legal mortgage is executed.

(3) Assignment Over Life Policies

Ninety percent of the surrender value is to be used provided confirmation of surrender value from the insurer is available and the assignment in the bank's favour is duly registered.

(4) Lien Over Fixed Deposit/Savings Deposit

Full account of the deposit may be used provided the depositor has duly signed a lien in the bank's favour.

(5) Deposit of Certificates of Deposit

Paid-up value minus 3 percent stamp duty on the face value is to be used.

(6) Assignment of Shares

(a) Quoted

Normally, 90 percent of the latewt market price is to be taken. Appropriate discounts should be considered if the shares are either thinly traded and/or comprise a large block of shares. Premiums may only be considered where there is a valid offer at the highest price as evidenced by a firm commitment, such as, purchase contracts or undertaking letters provided by brokers. If trading has been suspended (other than temporary suspension), the net tangible asset value, as per the latest audited financial statements (not more than 18 months old), is to be used provided an auditors certificate evidencing the value per share is available. If appropriate financial statements/certificates are not available, no value is to be given. In the case of shares where sales are temporarily suspended, the last quoted price prior to suspension may be used.

(b) Unquoted

Value may be given provided the shares are marketable. Appropriate value may be determined on the basis of 75 percent of the net tangible asset value per shares as certified by the company's auditors. A higher valuation may be given only if there is a firm purchase commitment as evidenced by purchase contracts or undertaking letters provided by brokers.

(7) (*a*) Mortgage Over Plant, Machinery and Equipment

In the absence of a professional valuation the net book value calculated by using a 20 percent depreciation rate on the straight line basis taking into account the date of acquisition and the acquisition price would be applicable.

(*b*) Mortgage over Motor Vehicles, Motor Cycles and Farm Power Equipment

In the absence of professional valuation the net book value calculated by using a 25 percent depreciation rate on the straight line basis taking into account the date of original registration and the acquisition price on that date, would be applicable.

(08)Pledge over Stocks/goods under the Bank's Control

Fifty percent of the market value determined on a case-by-case basis may be applicable.

(9) Hypothecation of Stock-in-Trade

Thirty percent of the current value of stocks provided that the level of stock-in-trade is closely monitored by the bank.

(10)Assignment of Book Debts

Generally, no value may be assigned unless the bank is certain and can prove that the debtors are worth the value quoted.

(11)Debentures

No value can be attached unless it is certified by a receiver/liquidator/ auditor/ Professional value.

(12)Guarantees

(*a*) Personal

Generally, no value, if such guarantee is unsupported. If supported by security mentioned above, the relevant security valuation base may be applied.

(b) Licensed Banks/Banks Abroad or Any Other Banking Institutions

Full value.

(c) Government Guarantee

Full value.

(d) Others

To be considered on a case by case basis.

(13)All Other Securities

To be considered on a case by case basis this should be documented in the relevant credit file.

ANNEX 3

Key Financial Indicators of Banks Included in the Sample
The key indicators of the Banks in the sample and the industry as at 12 December 2005 were as follows:

(LKR Million)

Bank	Total Advances	Non Performing advances (NPA)	Total provisions	Total Assets	Risk Weighted Assets (Loans)	Capital Adequacy Ratio In %	Capital Funds
A	184,010	20,438	10,313	319,504	102,675	13.2	16,183
B	124,433	7,367	2,192	180,078	88,446	12.0	15,768
C	114,719	10,403	6,242	166,012	86,521	11.5	11,239
Total of three banks	437,154	38,208	18,747	685,638	277,642	-	43,190
Commercial Banking Industry	920,608	81,856	44,164	1,465,167	-	12.4	101,156
Three banks as a % of Commercial Banking Industry	47.4	46.6	42.4	46.7	-	-	42.6
Banking Industry (LSBs & LCBs)	1,035,605	93,850	46,490	1,783,449	-	13.0	130,556

CHAPTER 5

ASESSING CAPITAL ADEQUACY OF THAI BANKS VIA BOOTSTRAP

by

Don Nakornthab and Amporn Sangmanee*

1. Introduction

Beginning at the end of 2008, the Bank of Thailand (BoT) will enforce a new capital adequacy framework of the New Basel Capital Accord (Basel II) on all commercial banks operated in Thailand. Basel II is an improvement over the current regulation (Basel I)[1] by making bank capital requirements better reflect actual risks and increased sophistication in financial markets. The new framework also emphasizes the role of supervisory authority and market discipline in ensuring that banks have proper risk management systems and enough capital relative to their risk exposure. The details on Basel II and its three pillars (minimum capital requirement, supervisory review, and market discipline) can be found in Basel Committee (2004). The details on Thailand's adaptation of Basel II can be found in Bank of Thailand (2005). Table 5.I shows implementation time frame of Basel II in Thailand.

At the time of this writing, no banks have submitted to the BoT their intended Basel II implementation plans (the submission deadline is end June 2006). Nevertheless, with regard to credit risk capital requirement, it is widely expected that, most Thai banks, like many of their SEACEN counterparts, will opt for the simplest Basel II approach; namely, the Standardized Approach (SA). The SA approach is similar to the current Basel I credit risk capital approach in that risk weights are assigned to different types of assets, but with more refined risk buckets and links to external credit ratings. It is well known however that the majorities of obligors in any bank portfolio are unrated and will receive the same risk weight as in Basel I. This is especially true for banks in Thailand as well as those in the SEACEN region. As a result, the credit risk capital charges calculated by the SA approach will not be much different from those calculated

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7. The BOT adopted Basel I and its 1996 Amendment in 1993 and 2005, respectively.

Table 5.1
Thailand's Basel II Implementation Timeframe

Year	Description
2005	The BOT issued a series of consultative papers and conduct on industry hearing.
2006	Final draft of Basel II framework issued (March). Banks to submit Basel II implementation plans (June).
Year end 2007	Begin parallel calculation of Basel I & II.
Year end 2008	Begin new Basel II capital changes (SA and FIRB).
Year end 2009	Begin new Basel II capital changes (AIRB and AMA).

Source: Bank of Thailand Supervision Report 2004. SA, FIRB, AIRB, and AMA stand for Standardised Approach, Foundation Internal Ratings-Based Approach, Advanced Internal Ratings-Based Approach, and Advanced Measurement Approach (for Operational Risk), respectively.

by the current approach. In short, it is almost a foregone conclusion that Basel II's intended objective of risk sensitivity will only be marginally achieved with the SA approach.

To achieve greater risk sensitivity, banks will have to rely on their own internal risk ratings of their obligors and move towards the more advanced approach to credit risk capital, the Internal Ratings-Based (IRB) approach. Although this is probably the ultimate direction that most Thai banks are striving for, the data and system requirements for IRB compliance are tremendous and it will take some years before they are ready for this approach.

In the transition period from SA to IRB compliance, it would be beneficial for central banks to have some ideas about the levels of capital that are commensurate with risks in banks' credit portfolios. In this paper, we ask whether it is possible for the BoT to use bank supervisory data to assess such information. The approach we have taken here is the one proposed by the Bangko Sentral ng Pilipinas (BSP) and agreed upon by participating country researchers in the First SEACEN Workshop on "Adequacy of the Existing Levels of Capital Implied by the Basel Standards, Relative to the Credit Risk Exposures of Banks in the SEACEN Region" held in July 2005 in Kuala Lumpur, Malaysia.

The rest of the paper is organized as follows. Section 2 describes the methodology and the data used in this study. The specificities of the Thai case are emphasized. Section 3 presents and discusses the results. Section 4 provides concluding remarks.

2. Methodology and Data

The methodology in this study is the one proposed by the Bangko Sentral ng Pilipinas (BSP). The BSP methodology (details in the Philippines' country paper) relies on the use of bootstrap to generate the empirical loss distribution of a bank's loan portfolio. The methodology has its root in the paper by Majnoni et al. (2004) who simulate by means of bootstrap the credit loss distributions of banks in Argentina, Mexico, and Brazil.

It is important to note that while the BSP and the Majnoni et al. approaches both exploit bootstrap in the simulation of the loss distribution, they differ materially in what they actually simulate. By classifying loans into two categories according to whether they have maintained their initial status or have defaulted over the following twelve months, what Majnoni et al. simulate in their study is the interaction between exposures at default and default occurrences. They then use the assumption of fixed loss given default to recover the portfolio loss distribution[8]. In contrast, what we will simulate in this study is the distribution of the amount of portfolio loan loss provision. The underlying idea is that the amount of loan loss provision associated with each obligor is a proxy for expected loss of that obligor and hence simulation will recover the portfolio loss distribution.

The BSP procedure is simple. Suppose that the data set of Bank A contains 1,000 obligors, each with an associated amount of loan loss provision. From this data set, we draw with replacement a sample containing 1,000 obligors and sum up the total amount of provision in the sample. This step is repeated a large number of times[9] to ensure the stability of the simulated distribution. Figure 5.1 shows the frequency distribution of simulated portfolio provision obtained by the

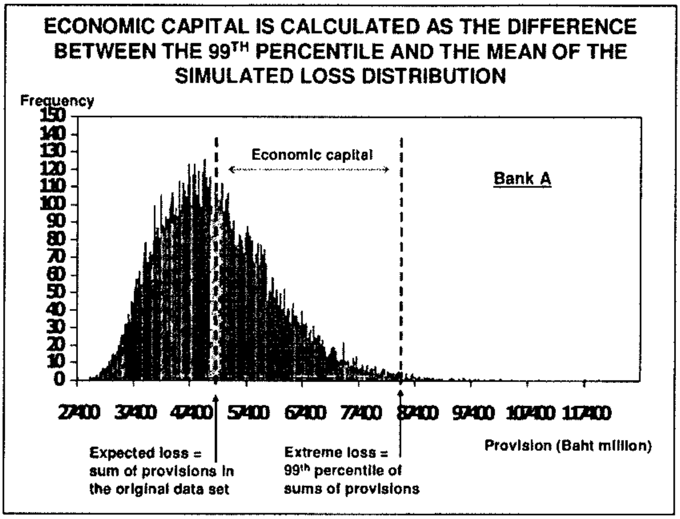
8. Mathematically, the portfolio loss variable is defined as the sum of the products of exposure at default (EAD), the loss given default (LGD), and the default indicator of each obligor in the portfolio, *i.e.*,

$$\widetilde{L}_{PF} = \sum_{i=1}^{m} EAD_i x LGD_i x 1_D$$

9. In this study, we set the number of repetition at 25,000.

BSP procedure for one of Thai commercial banks. The amount of implied economic capital is then calculated as the difference between the 99th percentile and the mean of simulated loss distribution.

Figure 5.1
Simulated Loss Distribution of Bank A



The final step is to divide the amount of the implied economic capital of this portfolio by the outstanding amount of loans in the original data set. The resulting capital ratio is denoted by $K_{Bootstrap}$. It is this ratio that we will use to compare with the regulatory capital adequacy ratio.

The data we use in our study is from the BoT DMS database. Beginning in October 2003, commercial banks in Thailand are required to transmit electronically certain data to the BoT on a quarterly basis. The database is managed by the BoT Data Management Department and is available for internal use only. For interested readers, the DMS dataset document can be downloaded from the BoT DMS website.[10]

10. http://www.bot.or.th/bothomepage/databank/Financial_Institutions/DMS/report.htm

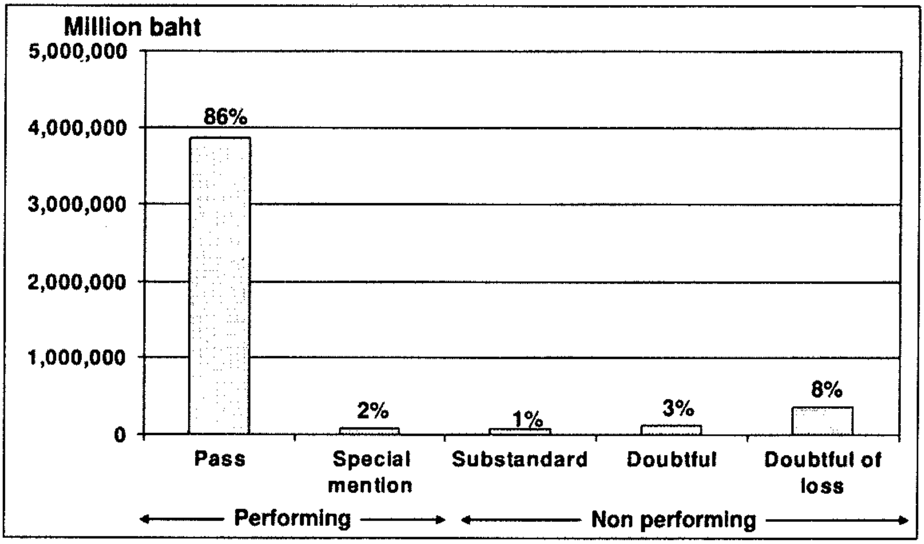
Available in the DMS extensive database is account-specific information for loans with original outstanding amount greater than 20 million baht (about USD 500,000). The information includes outstanding loan balance, the amount of deductible collateral[11], and the account classification status.

For readers unfamiliar with the BOT regulation, bank loans are classified into six categories: pass (or normal), special mention, substandard, doubtful, doubtful of loss, and loss. Loss loans are those considered irrecoverable and must be written off. The rest are classified according to a combination of aging and quality criteria. At first cut (aging criteria), pass loans are loans that have no interest overdue (or have overdue not more than 1 month in the case of overdraft loans). Special mention loans have interest overdue more than 1 month, but not more than 3 months. Substandard loans have interest overdue more than 3 months, but not more than 6 months. Doubtful loans have interest overdue more than 6 months, but not more than 12 months. Doubtful of loss loans have interest overdue more than 12 months. Beyond the aging criteria, there are quality criteria that look at projected cash flows and the ability of the debtor to repay the debt in entirety. For more details of these classification rules, the readers are advised to consult the Notification of the BoT Re: Worthless or Irrecoverable Assets of Commercial Banks, dated 28 February 2003. Effective fourth quarter 2002, non-performing loans (NPLs) are defined as the sum of substandard loans, doubtful loans, and doubtful of loss loans, plus fully provisioned loans that had previously been written off but not yet recorded in the accounts. Figure 5.2 shows the distribution of loan classes for all Thai commercial banks at the end of 2004. It is readily apparent from the figure that most performing loans are pass loans while most nonperforming loans are in doubtful of loss category. It is worth noting here that the majority of these doubtful of loss loans are "die-hard" NPLs that have lingered on Thai banks' balance sheets for several years.

For prudential purposes, all loans on bank's balance sheet are required to maintain minimum loan loss reserves or provisions against them. Pass, special mention, substandard, doubtful, and doubtful of loss loans are subject to a minimum

11. Amounts of deductible collateral are actually reported on a per-customer basis, as opposed to per facility. For practical implementation of this exercise, when a customer has more than one loan facilities, we sum up the balances of all facilities and assign the lowest classification status among the facilities to the aggregated amount.

Figure 5.2
Distribution of Bank Loans bv Loan Class. December 2004



Note: Excluding loans to financial institutions
Source: Thai banks' 2004 annual reports

of 1%, 2%, 20%, 50%, and 100% provisions. Provisions are calculated net of deductible collateral. If the amount of deductible collateral is more than the amount of outstanding loan balance, then no provision is needed[12].

To compute the amount of required provision for each account in our exercise, we use the following formula:

Required provision = max (0, provision rate x (outstanding loan amount less deductible collateral))

12. We would like to note here that to bring Thailand's prudential standard up on par with international best practices, the BoT has a plan to phase out the use of collateral value deduction in the calculation of required provisions.

Tables 5.2 and 5.3 shows descriptive statistics on outstanding balances and required provision amounts, respectively, for the ten banks[13] we use in this study. The information in both tables reveals highly skewed distributions.

Table 5.2
Summary Statistics on Outstanding Balances of Loan Accounts in the Simulation Exercise, December 2004

Bank	No. obs.	% of bank-wide portfolio	Mean (Bt m)	Median (Bt m)	Mode (Bt m)	Standard deviation (Bt m)	Min (Bt m)	Max (Bt m)
A	6,757	78.6	101.53	29.51	20.00	434.95	0.01	20,482.98
B	4,347	77.2	170.09	33.37	20.00	1,457.78	0.01	82,763.15
C	4,965	57.5	67.00	27.29	20.00	232.87	0.01	7,440.00
D	3,123	56.6	102.01	27.11	20.00	376.30	0.01	7,391.22
E	3,411	69.2	85.85	28.21	20.00	485.39	0.01	25,451.43
F	4,327	72.9	88.93	27.37	20.00	389.91	0.01	19,695.82
G	1,299	65.3	66.70	38.00	20.00	167.50	0.02	2,715.98
H	1,218	86.6	237.52	55.72	30.00	3,539.18	0.01	122,683.79
I	121	26.8	103.54	35.03	N/A	165.55	0.01	969.81
J	158	74.7	215.58	44.38	20.00	1,163.64	0.01	14,500.00

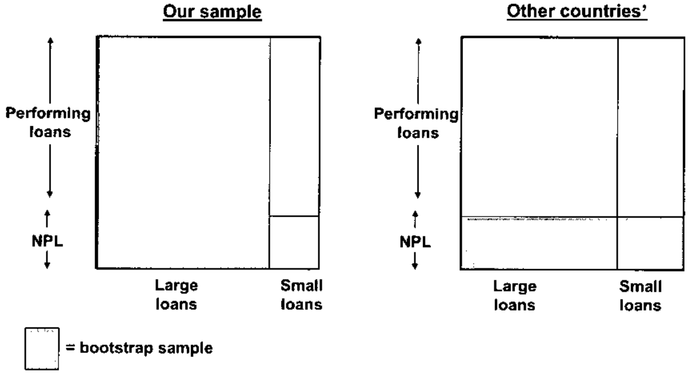
13. As of end 2004, Thailand had 12 commercial banks. Two bank however did not report the amount of deductible collateral and therefore were dropped from this study.

Table 5.3
Summary Statistics on Required Provision Amounts of Loan Accounts in the Simulation Exercise, December 2004

Bank	No. obs.	Mean (Bt m)	Median (Bt m)	Mode (Bt m)	Standard deviation (Bt m)	Min (Bt m)	Max (Bt m)
A	6,757	7.68	0.091	0	122.34	0	8,672.89
B	4,347	9.37	0	0	118.11	0	5,448.09
C	4,965	2.88	0	0	19.36	0	500.01
D	3,123	1.95	0.016	0	14.27	0	453.00
E	3,411	3.84	0	0	41.03	0	2,113.88
F	4,327	18.84	0.472	0	63.01	0	1,392.00
G	1,299	4.87	0.012	0	41.07	0	1,327.70
H	1,218	3.20	0	0	15.19	0	145.00
I	121	4.56	0.008	0	93.20	0	3,008.06
J	158	19.17	0.005	0	56.75	0	484.91

We would like to note here one crucial difference between our dataset and those used in other country papers. Our dataset contains both defaulted and non-defaulted accounts, but only for loans with original outstanding greater than 20 million baht. On the contrary, other countries datasets contain only defaulted or close-to-default (special mention) and defaulted loans. Figure 5.3 shows graphically the difference.

Figure 5.3
The Thai Dataset Compared to Those in Other Country Reports



3. Results and Discussions

Table 5.4 shows the value for $K_{Bootstrap}$, the implied economic capital ratio calculated by the methodology outlined in the previous section. Also shown are the implied expected loss rates (the ratio of provision to outstanding of the original data set) of the sample portfolios.

Table 5.4
Expected Loss Rates and $K_{Bootstrap}$, Full Samples

Bank	EL IN %	$K_{Bootstrap}$ IN %	Percentage of defaulted loans in the sample
A	7.6	4.7	17.4
B	5.5	3.1	14.3
C	2.9	0.8	7.5
D	4.8	2.1	12.0
E	3.4	1.1	10.0
F	4.3	2.1	10.5
G	21.3	5.6	30.2
H	1.9	3.7	3.9
I	18.5	15.0	54.7
J	1.5	1.8	7.6

It is clear from Table 5.4 that expected loss figure depends on the proportion of defaulted (substandard, doubtful, and doubtful of loss) loans in the sample portfolio. Banks with higher proportion of defaulted loans in the sample also have higher value of expected losses. Furthermore, for most banks, the proportions of defaulted loans are similar to their bank-wide NPL ratios[14]. For these banks, expected loss figures can be considered as representative for the banks.

14. There are a few banks for which the proportions of defaulted portfolio differ markedly from their bank-wide NPL rates. Because of confidentiality reasons, we cannot disclose banks' actual NPL ratios.

Except for Bank I, the calculated values of $K_{Bootstrap}$ vastly come below the current minimum capital ratio of 8.5%. In our opinion, these values of $K_{bootstrap}$ are too low to be regarded realistically as economic capital ratios for Thai banks.[15] The fact that our data sets cover only "large" loans does not seem to be the cause of this underestimation. In general, it is the "large" loans that have higher unexpected loss rates than "small" loans. If we had also small loans in our original samples, the problem of underestimation could be magnified.

We think there are two possible explanations for this underestimation. The first is that that required provision rates are poor proxies of expected loss rates. The second concerns the limitations of bootstrap as applied to this particular dataset.

There are many reasons to believe that regulatory provision rates are not good proxies of expected loss rates. First of all, it is only the minimum. Banks are free to provision more than the required level. Second, these rates are somewhat arbitrary. As far as we know, there is no formal statistical test to back them up. Third, the required provision rate for pass loans ignores the possibility of credit quality deterioration. Altogether, this means that required provision rates not only are poor proxies of expected loss rates, they understate them. This conclusion is consistent with a casual observation that all banks in Thailand carry provisions more than the level required by BoT. They must somehow perceive the level of expected loss that is greater than the required provision amounts indicate. Ideally, if we had access to these actual per-obligor provision amounts, we could have got more accurate results from the simulation.

The second possible explanation for underestimation of economic capital concerns limitations of bootstrap as applied to this particular dataset. It is well known in the statistical literature that bootstrap may not work well with the tail of the distribution. This could potentially lead to the underestimation of the tail, and hence the implied economic capital.

In practice, to get reasonable approximation of the tail, we need to bootstrap over a period of several years, not just at one point in time as we do in this study. Without the time dimension, the bootstrapped results may be distorted.

15. We disregard the results of Banks I, for we think that the proportion of the sample portfolio relative to bank-wide portfolio (see Table 5.2) is too small to make meaningful inferences.

Unfortunately, data limitation prevents us to bootstrap across time. Lastly, we would like to note that the Thai banking sector was in a relatively good shape (in terms of new and reentry NPLs) at the end of 2004. So it may not be a surprise to see an underestimation of capital at risk.

On a final note, we also perform the same simulation using only data from defaulted (substandard, doubtful, and doubtful of loss) accounts. Here, we are interested to see what would happen if we limit the simulation to only defaulted accounts as in other country papers[16]. The results of these "NPL-only" simulations are shown in Table 5.5.

Table 5.5
Expected Loss Rates and $K_{Bootstrap}$, Defaulted Samples Only

Bank	No. obs.	EL IN %	$K_{Bootstrap}$ IN %
A	868	40.5	26.1
B	547	35.5	21.6
C	377	31.4	10.1
D	501	36.0	17.4
E	408	30.1	9.7
F	589	37.1	20.4
G	517	69.1	17.8
H	29	30.8	81.5
I	57	33.3	25.9
J	24	11.3	13.0

16. To be exactly in line with the Philippine country paper, another simulation exercise is done with also special mention accounts. The results are not much different from Table 5.5.

The results of Table 5.5 are in line with those found in the other country papers. This time, we find that the values of $K_{Bootstrap}$ vastly overstate the 8.5 percent regulatory ratio. Unfortunately, we think these results are not very useful. By drawing from a pool of already defaulted obligors, what we really simulate is the distribution of loss given default of the defaulted obligors only. Recall the definition of a portfolio loss variable in Footnote 1. There is really no connection between the values of $K_{Bootstrap}$ in Table 5.5 and the economic capital ratio of the bank's entire loan portfolio and we strongly caution drawing certain inferences and recommendations from these results.

4. Concluding Remarks

For bank supervisors, it is useful to be able to gauge the level of risk capital the banks are facing. The information will serve as a benchmark during the transition from Basel II SA approach to IRB approach. The bootstrap exercise in this paper is one attempt for the authority to do so.

Nevertheless, in our view, the approach we take in this paper is not suitable in the case of Thailand. The results we obtain seem to largely underestimate our prior of actual economic capital.

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CHAPTER 6

ADEQUACY OF THE EXISTING LEVELS OF CAPITAL IMPLIED BY THE BASEL STANDARDS, RELATIVE THE CREDIT EXPOSURES OF BANKS IN NEPAL

by
Sachin Jung Rayamajhi[17]

1. Introduction

The Basel Committee on Banking Supervision (BCBS) has issued last 26 June 2004 the revised framework for the *International Convergence of Capital Measurement and Capital Standards*, or more popularly known as Basel II. Basel II seeks to make the existing risk-based capital adequacy framework more risk-sensitive. As such, it introduced three (3) approaches by which banks may compute for their credit risk capital requirements, which are deemed to be more reflective of the level of credit risk in banks' portfolios.

The first approach is the standardized approach (SA). Under the SA, banks' capital requirement will depend on the credit risk ratings of their assets given by external credit risk rating agencies. The second approach is the foundation internal ratings-based (IRB) approach. Under the foundation IRB, banks' internal credit risk rating systems will have to produce the probability of defaults (PDs) of the banks' assets, and plug these PDs into the complex credit risk algorithm designed by the BCBS. Lastly, the third approach is just a variant of the second approach. However, under this so-called advanced IRB approach, banks' internal credit risk rating systems need to supply not only PDs, but also information on loss given default (LGD), exposure at default (EAD), and effective maturity (M) into the credit risk algorithm.

Most, if not all, banking supervisory bodies in the SEACEN region have signified their intention to adopt Basel II. The region, however, may encounter difficulties in implementing any of the three approaches described above. For one, the limited number of rated claims in the SEACEN region will effectively render the standardized approach less effective. The two IRB approaches, on the other hand, appear too complex for both banks and banking supervisors in the region to immediately implement in view of their data requirements. Note

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that the complex credit risk algorithm prescribed under these approaches was calibrated using data from developed countries, which were not necessarily available in the developing countries in the region. Moreover, there is unequal access between banks and supervisors to any information available since many of the countries in the region have no credit bureau or their credit bureaus have rather limited information. As such, the detailed and richer information available at the bank may not be available to supervisors. In fact, for most of the supervisors, the only data available are bank level data found in financial statements. In Nepal, banks are required to submit the comprehensive list of all borrowers on a quarterly basis.

Is it possible then for the supervisors to asses the adequacy of the existing levels of capital implied by the Basel Standards, relative to the credit risk exposures of banks in the SEACEN Region using these information?

This study tried to measure credit risk faced by banks using information on classified accounts found in the supervisory examination reports (ROE) and the Value-at-Risk approach. The resulting capital level can be compared with the capital level arising from the existing risk-based capital adequacy framework, to determine whether it is adequately covering for credit risk in the banking system.

2. Definition of Default

Nepal Rastra Bank (NRB), the regulatory body of all deposit taking institutions in Nepal requires the banks to classify their loan portfolio on an ageing (past dues) basis. NRB has identified four classifications with the following criteria.

2.1 Pass Loan

This category consists of loans that are not past due or due up to a period of 3 months. In addition, the loans that are extended against the security of gold, fixed deposit, government securities can be classified as pass loan irrespective of their past dues or expiry dates. These types of loan are also known as performing loans

2.2 Non Performing Loan (NPL)

All loans categorized as Substandard, Doubtful or Loss are classified as Non Performing Loans.

1. *Sub-standard Loan*

   This category consists of loans that are past due from 3 months to 6 months.

2. *Doubtful Loan*

   This category consists of loans that are past due from 6 months to 1 year.

3. *Loss Loan*

   This category consists of all loans that are past due by more than 1 year. The loans that meet the following criteria are also to be classified as loss loan irrespective of their past dues or expiry dates: (1) If the loan is unsecured; If the borrower is declared insolvent; If the borrower has disappeared or is absconding; (2) If the bills purchased or negotiated remains unsettled for 90 days. Similarly, if the force loans created out of Letter of Credit obligation or invocation of guarantees are not settled within 90 days, they are also to be classified as Loss Loans.; (3) If the auction for recovery has been in process for more than 6 months or the case for recovery is under litigation; (4) If the loan is extended to borrowers that are blacklisted by the Credit Information Center; (5) If the project/business cannot commence its operation or if the project/business is not in operation; and (6) If the credit card dues have not been written off within 90 days from due date.

3. Computation of Loan Loss Provision

NRB requires the banks to classify their loan portfolio and make provisions for possible losses on a quarterly basis. The banks are required to create provisions as follows:

S.No.	*Classification*	*Provision Rate %*
1	Pass	1
2	Substandard	25
3	Doubtful	50
4	Loss	100

However, in case of loans that have been extended to priority sector and are insured, only a quarter of the required provision is warranted. i.e. in case of priority sector loan falling under Loss category, only 25 percent provision is required.

The provision is calculated as follows:

Provision = Outstanding amount at the end of the quarter X Applicable Provision Rate based on the classification.

NRB does not allow the deductions towards the value or quality of the collateral while calculating provisions. However, the loans secured by liquid collaterals like government securities, gold and fixed deposit are allowed to be classified as pass loans irrespective of their past dues. Hence some recognition is granted on account of the collateral, though in an indirect manner.

4. Calculation of Capital on Current Risk Based System

NRB requires all banks to risk weight their assets and provide necessary capital at the end of each quarter. The assets are risk weighted on their gross values rather than their net values and the risk weights range from 0 percent to 100 percent depending on the risk profile. The capital adequacy ratio is as follows:

S.No.	*Criteria*	*CARin %*
1	Tier I Capital	6
2	Capital Fund	12

5. Methodology and Data

5.1 Methodology on Credit Risk Measurement

Credit risk is the risk of loss on a financial or non-financial contract due to the counterparty's failure to perform on that contract. Credit risk's two components are default risk and recovery risk. Default risk is the possibility that a counterparty will fail to meet its obligation, and recovery risk is the possibility that the recovery value of the defaulted contract may be less than its promised value.

Models that try to measure credit risk can be classified into four groups: the spot rate models, default models, credit rating models and asset models. These classifications group credit risk models according to how they explicitly or implicitly describe the default and recovery rate process. Most of the models however focus on modeling default rather than recovery.

Spot rate models. This first division of models attaches a price to credit risk and the dynamics of default is implied by the dynamics of the price of credit risk. The price of the credit risk is reflected in any of the credit risky spot rate, forward rate, or discount factor. These models focus on one of these three rates.

Default models. Models of this type directly model the risk of default and are closely related to the spot rate models.

Credit rating models. Credit rating models generalize default models. If in default models there are only two states, default and non-default, in this type of models, there is a state for each credit rating. The credit rating system is a linear ordering of creditworthiness. The rating could be assigned by a credit rating agency, implied by market prices of the firm's debt, or calculated or assigned through some other means. The lowest state usually represents default.

Asset model. This approach is a continuous state limit of the credit rating approach as exemplified by Black-Scholes and Merton model. In this approach, it is deemed that the corporation's asset is the sum of corporation's equity and debt. The firm goes into default when the value of the assets drops below the face value of the debt. Viewed this way, both the equity and debt are contingent claims on the total assets of the firm and their prices were modeled using the Black-Scholes and Merton option theory.

Examples of the default models and credit rating models are the KMVs Credit Monitor and JP Morgan's CreditMetrics, respectively. These are the models used in more developed jurisdictions and are largely based on equity or corporate bond prices. Both approaches however, have as their foundation Merton's asset value model which establishes a relationship between credit quality and asset value of the debtor firms. In Credit Monitor, the volatility of equity prices are used as inputs in determining the "distance to default", which is the difference between the value of a company's assets and a certain liability threshold. CreditMetrics, on the other hand, is a *marked-to-market* approach, which linked bond prices and ratings, and the probability distribution of future bond prices, and hence a description of credit risk, are calculated based on a ratings transition matrix.

Another default model is the CreditRisk+ used by Balzarotti et. al. (2002). Balzarotti used data from Argentina's *Central de Deudores* database, a public credit registry, in measuring credit risk in Argentine banks' loan portfolio.

Default models works well in jurisdictions with liquid equity markets. The applicability of this approach therefore, is limited in the SEACEN region. In addition, the default experiences of big corporate entities that characterize the equity markets are not reflective of the default scenario of SEACEN banks' loan portfolio, which are composed mostly of lending to the small and medium businesses. Balzarotti was able to use a default model given a small universe of quoted equities and a small number of rated and traded corporate bonds but with the use of a public credit registry. Public credit registries however, are either not existing or are wanting in terms of needed information in most SEACEN countries.

Credit rating models on the other hand, works well in markets with big pools of rated corporate bonds. The dearth of rated bond issuances in the region makes this approach not suitable for measuring credit risk in the banking system. Besides, those that issue bond instruments are mostly big companies, which again are not representative of the banking system's credit risk exposures.

5.2 The Simulation Procedure

Capital allocation system generally assumes that it is the role of reserving policies to cover expected credit losses, while it is that of economic capital to cover unexpected credit losses.

As mentioned, expected loss can be viewed as the summation of all provisions made at different credit classification categories. In most credit risk models expected loss for a certain credit facility is estimated as the product of expected default frequency (EDF), loan equivalent exposure (LEE) and expected loss rate given default (LGD), i.e. EL = EDF*LGD*LEE. EDF is replaced in some credit models with probability of default (PD). In the absence of information in estimating these complex measures, and with only the regulator's data on loan loss provisions, the expected loss can be crudely measured as an average of historical loss data of a bank's portfolio or of such portfolio's simulated loss data. The breaks however in the historical loss data (as measured by loss provisions) caused by changes in default definition and provision rates may render this approach less valid. This then leads to the second approach, that of simulation.

Several simulation procedures are available that can be classified as either parametric or non-parametric. Two of these approaches are the jackknife and the bootstrap. The bootstrap is a computer-intensive method developed by Bradley Efron and others to derive standard errors of estimates from information in the sample and do statistical inference. Bootstrap was adopted by Majnoni (2004) in estimating bank capital and in setting loan loss reserve regulation in his paper entitled "Bank Capital and Loan Loss Reserves Under Basel II: Implications for Emerging Countries". In this paper however, Majnoni used data from a public credit registry that contains information on a very large number of loans in the financial system of Argentina, Mexico and Brazil.

In the absence of such complete data on loans, an alternative is to simulate the distribution of credit losses for a bank using its own pool of classified accounts. The steps in the bootstrap methodology are as follows:

Step 1 : From the pool of classified accounts, a random sample of size n (n can be the total number of classified accounts of the bank in consideration) was taken.

Step 2 : From this sample, the total amount of provision was computed

Step 3 : These two steps was repeated r times. Since the concern is the estimation of the tail of the distribution, it is necessary to produce a large number of replicates such that r should be at least 1,000. In this case, the simulation was done 20,000 times.

Step 4 : From the simulated distribution, parameters such as the mean loss and variances were estimated and the maximum amount of losses that can be experienced from bank's classified accounts at 1 percent confidence level was computed using the Value-at-Risk (VaR) concept.

Since VaR is composed of both the expected and unexpected losses, the capital level, K_{cl}, that would be sufficient to cover banks' unexpected loss for classified accounts is given as the multiple of the standard deviation of the measured distribution.

Note that in the risk-based assessment of capital adequacy of a bank, the economic capital (accounting for credit risk alone) is determined by charging risk weights to almost all accounts (except sovereign accounts). However, for this study, only classified accounts were considered, hence, the incomparability of K_{cl} with the regulatory capital that can be derived from the economic capital reported by the banks. A more appropriate comparison would be between K_{cl} and the risk-based capital due from loans.

Note that K should serve as benchmark in assessing the sufficiency of economic capital set aside by bank for credit risk. It should be seen as the minimum amount of capital that will cover unexpected losses since K is estimated using the loan portfolio only, excluding other risk assets. In addition, banks are expected to account for other possible form of credit risk such as concentration risk. Thus, for the study, K should also be compared with the actual economic capital for credit risk as reported by bank in its CAR report.

5.3 Some Technical Notes on the Bootstrap Procedure

The bootstrap is a computer-intensive method developed by Bradley Efron (1979) and others to derive standard errors of estimates from information in the sample and do statistical inference. It is a type of Monte Carlo method applied based on observed data.

The most fundamental idea of the bootstrap method is the estimation of inference uncertainty from the estimated sampling distribution of the conceptual probability distribution f. In practical application, the bootstrap means using some form of re-sampling with replacement from the actual data, x, to generate B bootstrap samples, $\underline{x}^*$. Often the data (sample) consist of n independent units and it then suffices to take a simple random sample of size n, with replacement, from the n units of data, to get one bootstrap sample. However, the nature of the correct bootstrap data re-sampling can be more complex for more complex data structures.

The set of B bootstrap samples is a proxy for a set of B independent real samples from f. Properties expected from replicate real samples are inferred from the bootstrap samples by analyzing each bootstrap sample exactly as the real data sample is analyzed. From the set of results of sample size *B*, the inference uncertainties from sample to conceptual population are measured. The bootstrap can work well for large sample size (n), but may not be reliable for small n (say 5, 10, or even 20), regardless of how many bootstrap samples, *B*, are used (Efron, 1993).

The logic behind the bootstrap is this: All measures of precision come from a statistics' sampling distribution. The sampling distribution gives the relative frequencies of the values of the statistic when the statistic is estimated on a sample of size n from some population. The sampling distribution in turn, is determined by the distribution of the population and the formula used to estimate the statistic.

In some cases, the sampling distribution can be derived analytically. For instance, if the underlying population is distributed normally, and one calculates the means, the sampling distribution for the mean is distributed as t with n-1 degrees of freedom. In other cases, deriving the sampling distribution is too hard, as in the case of means calculated from non-normal populations. Sometimes, as in the case of means, it is not too difficult to derive the sampling distribution as $n \rightarrow \alpha$. The distribution of means converges to a normal. The asymptotic result is then used to calculate some measure of statistical precision on a finite sample of size n even though it is incorrect.

Mechanically, the procedure is this: One has a dataset containing n observations and an estimator which, when applied to the data, produces certain statistics. One draws, with replacement, n observations from the n observation dataset. In this random drawing, some of the original observations will appear once, some more than once, and some, not at all. Using the dataset, one applies the estimator and estimates the statistics. One does it again, drawing a new random sample and re-estimating, and again, and keeps track of the estimated statistics at each step of the way (called a replication).

6. Data Issues/Limitations

The data used for study are extracted from the audited financial statements of the banks. The Nepalese fiscal calendar ends on Mid July. So, these data relate to the classification as of Mid July 2005. In this study we used the data of 5 banks which account for 31 percent and 28 percent of banking industry's total loans and total assets respectively.

The classification of the assets and loan loss provision are created by the concerned banks on a quarterly basis. During the review of the banks' classification, some cases have been observed, where the classification requirements have not been fully complied with. However, in context of the overall banking industry, these variations are within satisfactory levels

The study did not include two largest banks of the country because of the lack of electronic data. These two banks account for the largest amount of NPA of the country. So, in the absence of the data of these two banks, the conclusion for the entire banking industry could be misleading.

The data used for this study reflect the classification of Mid July 2005 rather than over different time horizons. Thus, the result is only a snap shot of the credit risk at the point of time rather than over various time horizons. Likewise, this study is influenced by the present economic environment.

The study is limited to the classified accounts only and does not take into account the unclassified accounts, the risks relating to off balance sheet exposures and other operational risks related to credit risk. Thus, the estimated economic capital is surely an underestimate of the economic capital for the entire bank.

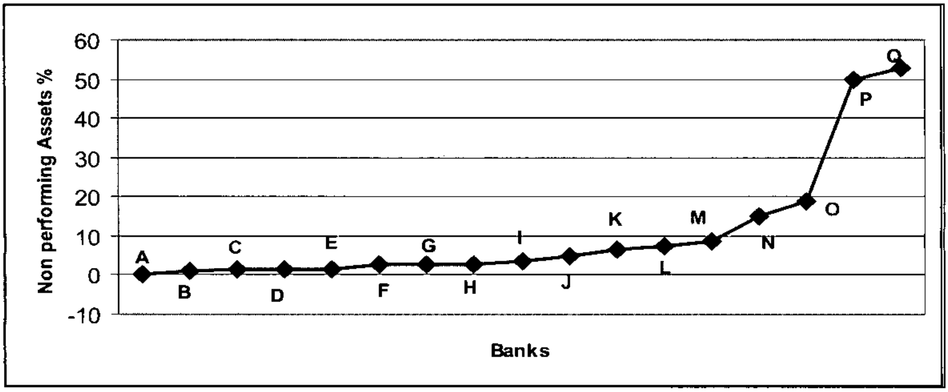
7. Results

The Nepalese fiscal calendar ends in Mid July of Gregorian calendar. In Nepal, two of the largest banks are government controlled (denoted by P and Q in the following chart) and the bulk of the non performing assets of the banking industry are concentrated in these two banks. The industry average of the gross non-performing assets of the bank as on Mid July 2005 was 19~~8.9~~ percent. If the NPA of the two largest banks are excluded, the industry average falls dramatically to 65.6 percent.

The non performing assets of the largest two banks were not available in electronic form and thus these banks were not considered for the study. The banks used for this study are indicated by red in the following chart.

Figure 6.1

Level of Non Performing Loans of Commercial Banks in Nepal



In this study, the classified accounts of five commercial banks have been used, mainly because of the low number of classified accounts in the banks. In majority of the banks, the total number of classified accounts was below 100. So, five banks where the classified accounts were more than 250 were selected for the study. Among these banks, Bank O has the highest proportion of NPA while Bank C has the lowest. These banks cumulatively account for 31.40 percent of the banking industry's total loan and 287.76 percent of the total assets respectively.

Table 6.1

Basic Statistics on Coverage of the Sample Banks on the Industry

Bank Id	% of Classified Accounts to Total Loan	% of Total Loan to Industry's Total Loan	% of Total Assets to Industry's Total Assets
C	1.32	7.44	6.30
J	4.99	4.20	3.62
L	7.44	9.14	10.22
M	8.64	4.08	2.75
O	19.04	6.54	4.87
Total	-	**31.40**	**27.76**

Table 6.2

Summary of Statistics on Provision of Classified Accounts

(Rs.In Thousands)

Bank	No.of Observation	Mean	Median	St.Deviation	Min.	Max
C	268	470.76	28.42	3,081.63	*	37,478.05
J	362	544.06	19.16	3,198.96	3.85	45,119.28
L	542	1,321.49	195.91	6,793.09	*	120,000.00
M	309	1,454.49	372.49	3,987.87	*	49,599.53
O	546	3,617.07	772.50	7,816.57	1.71	104,000.00

* Less than Rupees 1,000

All the sample banks under study exhibit longer right tail of the distribution. See Tables 6.1 and 6.2. Among these banks, Bank O has the highest number of classified accounts and the highest mean. Even though Bank L has the next largest number of classified accounts, its mean is relatively lower than that of Bank M because of high volume of classified accounts in Bank M.

When the results of the simulation are broken into the expected losses (EL) and the unexpected losses (UL), it is clearly visible that the majority of it is the expected losses for which the banks have provided for.

The graphical distribution of the simulated distribution of the banks is presented in Annex 1.

Table 6.3
Summary of Simulation Result
(Rs.In Million)

Bank	**Mean (EL)**	**Standard Error**	**95%**		**99%**	
			VaR	**UL**	**VaR**	**UL**
C	125.22	50.48	224.17	98.95	255.27	130.04
J	196.95	61.19	316.88	119.93	255.27	58.32
L	750.27	156.60	1,057.20	306.96	1,153.70	403.42
M	449.44	70.11	586.86	137.42	630.04	180.60
O	1,644.30	180.68	1,998.50	354.15	2,109.80	465.45

The value at risk, expected losses and the unexpected losses of the banks at both confidence intervals are then divided by the total portfolio of the bank to arrive at the estimates of the required capital. Among the banks used for this study, Bank O has the highest proportion of the value at risk and the unexpected losses. This is consistent with the trend in the percentage of classified accounts to total loan portfolio.

Table 6.4
Comparative Estimates of Value-at –Risk in Percent to Total Loan Portfolio (Rs. In Million)

Bank	Total Portfolio	95%			99%		
		VaR %	EL %	UL % K_{cl}	VaR %	EL %	UL % K_{cl}
C	10,946.73	2.05	1.14	0.90	2.33	1.14	1.19
J	6,182.04	5.13	3.19	1.94	4.13	3.19	0.94
L	13,451.17	7.86	5.58	2.28	8.58	5.58	3.00
M	6,011.90	9.76	7.48	2.29	10.48	7.48	3.00
O	9,626.91	20.76	17.08	3.68	21.92	17.08	4.83

The results in Table 6.4 above indicate that at both confidence intervals, the amounts of capital the banks are expected to hold as cover for the unexpected losses are within the CAR of 8 percent prescribed in the Basel document.

8. Conclusion

The simulation of the credit loss distribution using the data on classified accounts is based on the assumption that provisions cover expected losses and banks should hold capital to cover unexpected losses.

In Nepal, under the current risk based system, banks are required to risk weight their assets in gross values rather than the net values. The banks do not get the deductions for the general loan loss provision or the interest suspense in the calculation of capital adequacy. Moreover, at present, the banks are expected to maintain CAR of 12 percent. So, as per the provisions of Basel II framework, the banks in Nepal will most likely get a capital relief in terms of allowances for specific provisions.

The result clearly indicates that the level of capital prescribed by the Basel Standards is sufficient to provide protection to the banks in Nepal. However, we must consider the limitation of the data used for the study. Thus, before making any policy recommendation, this methodology needs to be implemented in more banks and the study should be based on the data over different time horizon.

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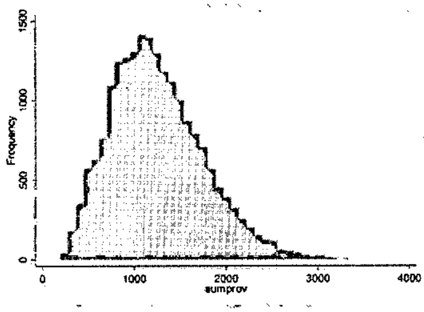
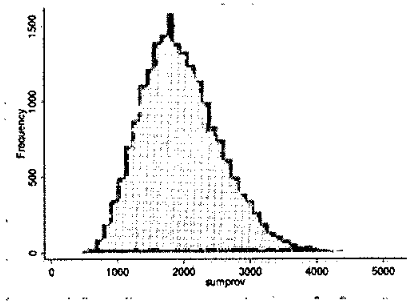
Annex 1

Distribution of simulated loss data

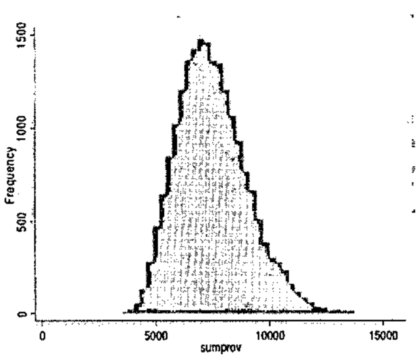
Bank C



Bank J



Bank L



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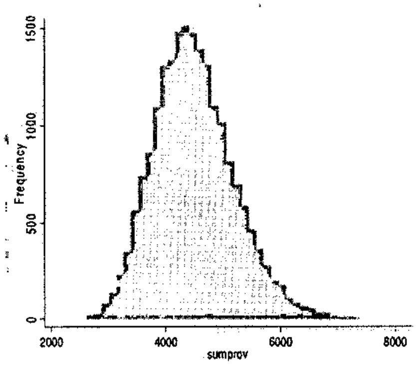

Bank O