Loan Loss Provisioning Methodology on Non-Performing Loans of Malaysia's Commercial Banks: A Longitudinal Panel Data Analysis Using Econometric Modelling

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ABSTRACT

The purpose of this paper is to research to come up with factors that determine loan loss provisions of non-performing loans of commercial banks in Malaysia, that is, factors reflecting the collectability of defaulted loans so that financial statements of banks reflect their true underlying risk conditions.

The results of research show among explanatory variables, bad debt recoveries as a factor to determine loan loss provisions that reflect the collectability of the defaulted loan, is rejected. The variable is a biased and inconsistent estimator. In the context of perceived credit risk - an estimate of recoveries has not fulfilled a perception of credit risk in the collectability of defaulted loans. On the other hand, non-performing loans as a factor to determine loan loss provisions that reflect the collectability of the defaulted loan, is not rejected. It is proven that it is not a biased estimator.

Keywords: Financial crisis, commercial banks, non-performing loans, loss provisions, bad debts, defaulted loans, and recoveries.

INTRODUCTION

In giving out borrowings to borrowers, there is a chance that banks not able to collect back the loans as the borrowers may default in repayment. If it happens, part or full amount of the loans may not be able to be recovered. Therefore, banks are required by banking regulators to make appropriate provisions for losses from the defaulted loans. This is when not likelihood banks would be able to collect part or all amounts due - principal and interest - according to contractual terms of loan agreement. Loan loss provisions (LLP) is defined as "a method that banks use to recognise a reduction in the realizable value of their loans" Podder and Al Mamun (2004).

The guidance for loans that are in default status, its classification and the required provisions are often set by the supervisory body on banks and financial institutions in each country. In Malaysia, is set by the Bank Negara Malaysia. The supervisory body in the country, for "financial years beginning on and after 1 January, 2010 has issued new guidelines that set out the minimum requirements on the classification of impaired loans and provisioning for loans impairment" www.osk.com.my that is enforce on all commercial banks.

Classification of loans/financing as impaired.

In the new guideline from Bank Negara Malaysia (BNM) issued and effective from beginning 1 January, 2010, www.bnm.gov.my, “a loan is classified as impaired where the principal or interest/profit or both is past due for more than 90 days or 3 months” when loan loss provisions is set at 20%.

The purpose of the research is to come up with factors that determine loan loss provisions of non-performing loans of commercial banks in Malaysia. This research problem arises because presently the factors being used to determine loan loss provisions do not produce an amount reflecting the collectability of the defaulted loans. Consequently, the financial statements of the banks do not reflect “faithfully”, www.ifrs.org their true underlying risk conditions.

LITERATURE REVIEW

From reviewing of literatures on loan loss provisions, two classification models are discovered that formed the basis of themes or schools of thought to solve the research problem. The two classification models are;

1. perceived credit risks as the basis to make credit judgments; and

2. opposing incentives which loan loss provisions are used by banks to achieve certain objectives.

Perceived credit risks as the basis to make judgements.

Dermine and Carvalho (2006) who reviewed the methodologies in calculating loan loss provisions found evidence that it is a key credit risk input in calculating bank’s profitability, capital adequacy, and solvency, and it is a key ingredient of “mark-to-market accounting.” Dermine and Carvalho have developed two methodologies in calculating equitable amount of provisioning for loan losses, at and after, default dates. The authors applied two methodologies on private real data of non-performing loans provided by biggest privately-owned bank in Portugal, Banco Comercial Portugues (BCP) contained total 374 defaulted loans. Most of these are to “small and medium size companies” and analysis covering from “June 1995 to December 2000” Dermine and Carvalho. From their studies, the authors raised two measurement issues on credit risk and loan loss provisions. First, “criterion” that defines “the time of default” as it is an “event” of significant important in loan loss provisioning, due to the “likelihood of being repaid diminishes as time elapses after the default date” Dermine and Carvalho. Furthermore, according to the authors, different classifications would lead to different results. Second, is the “method” that measures “the recovery rate (of the defaulted loans)” Dermine and Carvalho.

Opposing incentives which provisions of loan losses are means in achieving certain objectives.

In extending the subject matter to a wider discipline where it has implications, Dermine and Carvalho (2006) discovered loan loss provisions an essential ingredient of mark-to-market accounting. It indicates existence of active markets with determinable market prices. In view of the roles of loan loss provisions in the active markets, it is helpful to know the various opposing incentives that provisions of loan losses are means in achieving certain objectives.

In another study, Anandarajan et al. (2005) in their research on loan loss provisions of Australian banks have divided literatures on loan loss provisions based on their usage. The author divided the literatures into three uses, namely: 1) for earnings management, 2) for capital management; and 3) as a tool for signalling.

In this research study, the literatures have categorized into three categories, namely; earning and capital smoothing, signalling tool; and "time lag" Dermine and Carvalho (2006), between when credits start to grow and loans begin to default.

Earnings and capital smoothing management

A series of banking literatures analysed scope in pro-cyclical loan loss provisioning issues, that is, higher provisioning (amount) during better economic climate and lesser provisioning (amount) during economic downturn. Ismail et al. (2005) in their studies on whether banks in Malaysia manage earnings, defined earnings smoothing behaviour as a behaviour that exhibits earnings did not dip and rise according to actual performance. As a consequence, the banks' earnings show little fluctuation from one year to another.

Signalling tool

Dermine and Carvalho (2006) found evidence in studies of "Musumeci and Sinkey (1990) and Elliott et al. (1991)". The latter proved in the case of, "unexpected (announcement of) provisions", "at first counter-intuitive"; however, the announced "result is interpreted (by investors) as a signal that future earnings will be good" (Wahlen 1994). This attempt brings about positive impacts on bank stock returns. In the same vein, Ismail, Shaharudin and Samudhram (2005) were of the view that stability of banking sector is more of perception based than anything else.

Time lag between loan losses and credit growth

A third category of literatures on loan loss provisions, Dermine and Carvalho (2006) referred to studies by Jimenez and Saurina (2005) analysed the time lag between loan losses and credit growth, found stacking of provisions in times of economic growth. In view provisioning of loan losses involves stacking of reserves during good economic times to be used to absorb losses experienced during economic downturns, the process is almost similar to dynamic provisioning. According to Balla and McKenna (2009), dynamic provisioning is synonymous to statistical and countercyclical provisioning. The reason is that timing facilitates banks "incremental building of reserves during good economic times (with concurrent rise in credit) to be used to absorb losses experienced during economic downturns", Balla and McKenna.

RESEARCH METHODOLOGY

In this study, the traditional or classical methodology of econometrics is employed that uses observational data on bank-specifics and macroeconomic factor peculiar to Malaysia. The data on bank-specifics are secondary data (Loan loss provisions, Non performing loans, bad debt recoveries, interest income, net profit; and loans & advances) of nine locally-incorporated and three largest, in terms of assets, foreign-owned commercial banks in Malaysia. Thus, there are nine (9) locally-incorporated commercial banks in the analysis.

The nine (9) commercial banks are;

i. Maybank (Malaysia) Berhad
ii. CIMB Bank (Malaysia) Berhad
iii. Public Bank (Malaysia) Berhad
iv. RHB Bank (Malaysia) Berhad
v. AmBank (Malaysia) Berhad
vi. Hong Leong Bank (Malaysia) Berhad
vii. EON Bank (Malaysia) Berhad
viii. Affin Bank (Malaysia) Berhad; and
ix. Alliance Bank (Malaysia) Berhad.

EON Bank, on 9 May, 2011, became part of Hong Leong Bank following acquisition cost of RM5.06 billion of 100% stake, according to Kuen, 2011.

The three (3) largest foreign-owned commercial banks in Malaysia are;

i. HSBC Bank (Malaysia) Berhad,
ii. Standard Chartered Bank (Malaysia) Berhad; and
iii. Citibank (Malaysia) Berhad.

Secondary data is extracted from published annual reports as well as from the banks' web sites from 1996 to 2011. The macroeconomic factor is Gross Domestic Product (GDP), and the data is extracted from the website of the Malaysian Institute of Economic Research (MIER). The data is an example of a longitudinal panel data, where data are elements of both cross-sectional (i.e. 12 different banks), and time series (i.e. observations on the values that a variable takes at different time from 1996 to 2009). The total number of observations in the data is 168 panel data observations i.e. observations for 14 years for each of the 12 banks.

Theoretical framework and Hypothesis development

The dependent or regressand variable is "loan loss provisions"; and the independent or regressor or predictor variables are "non performing loans", "bad debts recoveries", "interest income", "net profit", "loan & advances"; and "Gross Domestic Product (GDP)". The independent variables, for several reasons, are theorized to provide information on determinants of loan loss provisions of the banks.

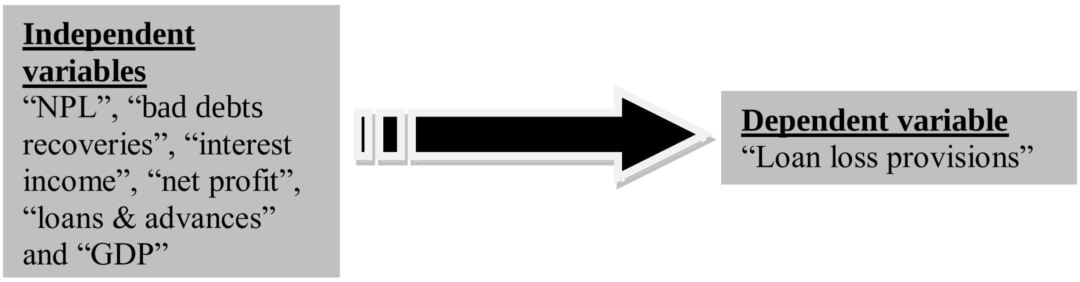
For instance, "recoveries of bad debts" is one of the independent variable in view of an estimate of "recoveries" would be used in the calculation of loan loss provisions of defaulted loans "n" months in arrears. In other words, the calculation to determine the expected losses in loan portfolios would be affected by an estimate of "recoveries". For example, an estimate of recoveries of 80% - 3 months and less than 6 months, after the days in arrears - would require loan loss provisions to be set at

20%. This is the amount to be set as loan loss provisions that is, an amount that is expected not to be recovered. In an earlier research, Podder and Al Mamun (2004) had used data on the recovery status from settlement of suits in proving that making too much loan loss provisions has no relation to recoveries.

In other recent studies, Balla and McKenna (2009) documented pro cyclical provisioning is event driven that is, to build up reserves during boom years when there is tremendous growth in loan and advances. Therefore, the authors who had researched on pro cyclical provisioning in Spain, are of the view that timing of provisioning is more important than level of provisioning. Gross Domestic Product (GDP) as an indicator to determine loan loss provisions is supported by the authors. The authors reported “from 1991-1999, Spain’s correlation between its loan loss provisioning levels and GDP was -0.97, the highest in the Organization for Economic Co-operation and Development (OECD)” Balla and McKenna. However, the authors opined this approach is backward looking.

Theoretical framework

In a schematic diagram below is the conceptual theoretical framework that visualizes the network of associations among the variables.



Estimation of panel data multiple regression models

In this analysis, a single stage equation panel data multiple regression models is used, that Ismail et al. (2005) referred in previous studies on earnings management of banks by “Ahmed et al. (1999), and Lobo and Yang (2001)”, this model “avoids under estimation of variable” Goldberger (1961). However, a classical linear regression model (CLRM) that assumes homoscedasticity i.e. constant or equal variance among the banks is not fulfilled in this study. This is due to “data cuts across different time periods” according to Ismail et al., over different banks. For larger banks, for instance, on the average reported “higher loan loss provisions than (that of) smaller banks” Ismail et al. Therefore, as Ismail et al. study on Malaysian banks’ earnings management through loan loss provisions, based on the characteristics of the data obtained, a Generalized Least Squares (GLS) method is deemed more appropriate in examining the relationships among the variables that are theorized to exist. As Gujarati and Porter (2009) indicated, in Generalized Least Squares (GLS), observations that come “from populations with greater variability are given less weight than those coming from populations with smaller variability”, thus it is capable of producing estimators that are BLUE (Best Linear Unbiased Estimator).

The regression model

$LLP_{it} = B_0 + B_1NPL_{it} + B_2RC_{it} + B_3II_{it} + B_4NP_{it} + B_5LA_{it} + B_6GDP_{it} + e_{it}$,

Where,

LLP = loan loss provisions, a dependent variable

i = 1,2,3,....12 (i.e. "i"= identity for 12 banks)

t = 1,2,3,.....14 (i.e. "t"= time for 14 years i.e. from 1996 to 2009)

B_0 = intercept that is mean or average value of Y (i.e. loan loss provisions) when NPL, bad debts recoveries, interest income, net profit, loans & advances, and GDP, are equal to zero

B_1 = partial regression coefficient that measures the mean value of LLP per unit change in **NPL** holding the values of bad debts recoveries, interest income, net profit, loans & advances and GDP constant

NPL = Non Performing Loan (NPL)

B_2 = partial regression coefficient that measures the mean value of LLP per unit change in **bad debts recoveries** holding the values of NPL, interest income, net profit, loans & advances and GDP constant

RC = bad debts recoveries

B_3 = partial regression coefficient that measures the mean value of LLP per unit change in **interest income** holding the values of NPL, bad debts recoveries, net profit, loans & advances, and GDP constant

II = Interest Income

B_4 = partial regression coefficient that measures the mean value of LLP per unit change in **net profit** holding the values of NPL, bad debt recoveries, interest income, loans & advances and GDP constant

NP = Net profit

B_5 = partial regression coefficient that measures the mean value of LLP per unit change in **loans & advances** holding the values of NPL, bad debt recoveries, interest income, net profit and GDP constant

LA = Loans & Advances

B_6 = partial regression coefficient that measures the mean value of LLP per unit change in **GDP** holding the values of NPL, recoveries, interest income, net profit and loans & advances constant

GDP = Gross Domestic Product (GDP) where GDP = 1 if the GDP for the year is higher than that of the previous year; GDP = 0, otherwise

e_{bt}= random error

FINDINGS

Fixed Effect Model

In a fixed effect model, it allows for heterogeneity features among the banks. All 168 observations are pooled each of the 12 banks has a different intercept. Although, each of the banks has different intercept, each bank's intercept does not vary over time, that is, it is time-invariant. Henceforth, this model is termed, "fixed effect".

The revised regression model is as follows:

$LLP_{it} = B_{0\mathbf{i}} + B_1NPL_{it} + B_2RC_{it} + B_3II_{it} + B_4NP_{it} + B_5LA_{it} + B_6GDP_{it} + e_{it}$, Where, subscript **i** on intercept term would suggest intercepts of 12 banks may not be same because of special features that are unique of banks in sample, such as different managerial philosophy, managerial style or loan appetite.

Fixed Effect Model

"Dependent Variable: LLP
Method: Panel Least Squares
Date: 12/23/10 Time: 15:29
Sample: 1996 2009
Periods included: 14
Cross-sections included: 12
Total panel (balanced) observations: 168" Eviews

	"Coefficient	Std. Error	t-Statistic	Prob. "
C	211453.5	44884.82	4.711024	0.0000
NPL	0.000743	0.003434	0.216402	0.8290
RECOVERY	-0.282042	0.188330	-1.497595	0.1363
INTINCOME	0.058446	0.020619	2.834550	0.0052
NPROFIT	-0.280696	0.052073	-5.390428	0.0000
LOANADV	0.004954	0.001921	2.579331	0.0109
GDP	22003.20	38721.22	0.568246	0.5707

"Effects Specification"

"Cross-section fixed (dummy variables)"

"R-squared	0.580588	Mean dependent var	328769.8
Adjusted R-squared	0.533055	S.D. dependent var	362087.8
S.E. of regression	247426.9	Akaike info criterion	27.77658
Sum squared resid	9.18E+12	Schwarz criterion	28.11129
Log likelihood	-2315.232	Hannan-Quinn criter.	27.91242
F-statistic	12.21432	Durbin-Watson stat	1.809449
Prob(F-statistic)	0.000000"		

In above results, average of the fixed effect for all the 12 banks is 211,453.5. Furthermore, the R^2 is higher at 0.58088 than the R^2 in pooled regression, casting some doubts on the results given earlier under pooled regression. However, this level of R^2 may not be very high; nevertheless this is expected when involving empirical observations consisting of cross-sectional data (banks) because of diversity among cross-sectional units (banks). Also, the values of slope coefficients in fixed effect model are different from that in pooled model.

F-test

The F-test is used to identify which is a better model, from the two models - pool or fixed - that fit to data set.
In testing the overall significance, i.e. the F-value is

$$= \frac{(0.580588-0.483170)/5}{(1-0.580588)/162} = 7.53$$

(Note: There are 168 observations and 6 regressors)

The null hypothesis is all differential intercepts are equal to zero with computed F value is 7.53, for 5 numerator and 162 denominator df, is statistically significant. Thus, the null hypothesis that all the differential intercepts are equal to zero is rejected. The conclusion is that all the 12 banks have different intercepts. It would appear fixed effect regression model is better than pooled model regression.

Random Effect Hausman Testing

Hausman test is employed to find out a better model, which of the two; fixed effect or random effect. In other words, to find out whether "random effects are uncorrelated with the explanatory variables"

Due to $X^2{}_{(6)}$ statistic for testing differences between all coefficients between the two models is $X^2{}_{(6)} = 21.525654$, is statistically significant with corresponding p-value = 0.0015, null hypothesis is rejected. The null hypothesis is fixed effect model estimators don't differ substantially from random effect model estimators. If null hypothesis were true (i.e, in that the estimators do not differ substantially), probability of obtaining a chi-square value of as much as 21.525654 or greater would be 0.15%. Additionally, in the last column of the table shows the "difference between the fixed effect and the random effect model" is statistically significant. Thus, this suggests that random effect estimates are probably correlated with explanatory variables resulted in inconsistent estimation of the regression coefficients. In other words, the fixed effect model seems a more preferred model than the random effect model especially so when in situations the individual-specific intercept may be correlated with one or more regressors.

CONCLUSIONS

The results showed that fixed effect approach seems a more preferred model due to its assumption that each of 12 sample banks has a different intercept. The model takes into account the heteroscedasticity variations among the 12 different banks, and their heterogeneous management styles across different time periods. This is in contrast to Sufian (2007) in his research on efficiency of Singapore's commercial banks who assumed all banks were sufficiently similar in resources, a condition that is difficult to fulfil. The results of Hausman test showed that among explanatory variables, bad debt recoveries as a factor to determine loan loss provisions that reflect the collectability of the defaulted loan, is rejected. The reason is that the variable is a biased and inconsistent estimator. In the context of perceived credit risk - the first classification model discussed in literature review - an estimate of recoveries, has not fulfil a perception of credit risk in the collectability of defaulted loans. This is in agreement with Podder and Al Mamun (2004) who discovered collection of bad loans has no relation to loan loss provisions.

Furthermore, the results of the analysis showed that there may be violation in the assumption in that the error term is not correlated with the regressors. In other words, the error term may be correlated with bad debt recoveries and henceforth, bad debt recoveries as variable that is unbiased and consistent estimator is rejected. On the other hand, non-performing loans as a factor to determine loan loss provisions that reflect the collectability of the defaulted loan, is not rejected. It is demonstrated that the variable is not a biased estimator. This is in agreement with Lin and Mei (2006) who discovered causal relationships between non-performing loans and loan loss provisions.

Implications for further research

Future research could be carried out on determinants of loan loss provisions of Islamic banks, stemmed from Taktak et al. (2010) findings that the Islamic accounting regulators actually encourage dynamic provisioning based on Islamic principles of *shariah*, i.e. risk sharing with investors. The authors reported use of "Profit Equalization Reserves (PER)" and "Investment Risk Reserves (IRR)" Taktak et al. (2010), as mechanisms for this purpose despite the wide spread view that they're actually meant to stabilize rewards to investors rather than to smooth results.

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