CAPITAL ADEQUACY ASSESSMENT WITH RESPECT TO MARKET RISK
(An Alternative Model)

By

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Abstract

This paper compares the results of capital adequacy ratio (CAR) calculated using stnadardised models and VaR. Using data from Indonesian banks, the results show that the CAR calculated using VaR can provide a lower of capital requirements, even though the calculation of CAR has accomodated the multiplication factors as required by BIS guidelines. Additionally, this study also found that the results of VaR very much depend on the distribution assumption in the volatility estimation and the adoption of confidence level. The adoption of VaR in banking industry will reduce the power of regulators to control banks because the calculation of VaR needs expertise and data which are not available at most of regulatory authority. The role of consulting firm and acedemician will be more significant in desiging models to improve the accuracy of risk estimation.

1. Introduction

A wide ranging series of deregulatory measure for banks in Indonesia was put into effect in October 1988. The deregulation package in 1988 includes the adoption of risk-based capital adequacy requirements, as proposed by the BIS (Basle Accord). However, many Indonesian banks suffered problems and some even failed. This provided evidence that risk-based capital adequacy regulation in Indonesia had failed to prevent banks from taking excessive risks. After a series of deregulation measures for the banking industry was put into effect, many banks suffered illiquidity at the beginning of the 1990s. As a result, the authorities (i.e. Bank Indonesia and the Finance Ministry) need to address the following issues: first, the authorities are apparently unable to detect financial problems in banks at an early stage; second, the authorities adopt imprudent capital adequacy regulation; third, the absence of a deposit insurance scheme creates costs for society when there is a bank failure.

Such observations provide the motivation for this research which seeks to identify the nature of bank risks in Indonesia and also analyses the operation of risk-based capital adequacy regulation in Indonesia.

To obtain a general view of risk in Indonesian banks, this study includes an empirical study to identify the determinants of problem banks in Indonesia. This study finds that credit risk and operational risk contributed significantly to banking problems. State banks, non-foreign exchange banks and regional development banks are shown to be also sensitive to interest rate risk. Foreign exchange rate risk is less significant for banks (by group) in Indonesia. If we examine cases individually, however, there were some bank failures which were due to foreign exchange rate risk. This paper excludes the discussion on the determinants of problem banks in Indonesia.

This study also analyses deficiencies of the BIS proposal 1988, such as focusing only on credit risk (ignoring market risk), using an arbitrary choice of risk weights and neglecting to consider risk correlation for diversified portfolios. In 1996, a new proposal was released as amendment to the Basle Accord of 1988. The new proposal is intended to cover risks arising from market risk factors. The discussion in this report also covers the problems that arise from calculating market risk using the BIS's standardised method, and suggests alternative methods based on theories of finance and econometrics. To provide evident that the models in this study are reliable, the results of empirical study will be included.

Mare recently, some efforts have been made to improve the situation, such as the adoption of new approaches in supervising banks (i.e. separation of on-site and off-site supervision) and the establishment of a team to study the adoption of deposit insurance and the improvement of capital regulation. This study will try to examine the issues related to capital regulation using finance theory. The main objective of this research is to develop a methodology for assessing market risk that provide the most accurate measure of market risk.

This paper will be organised in the following structure: Section 2 outlines the basic concept of market risk; Section 3 provides quantitative representation of market risk; Section 4 discusses application of market risk model in foreign exchange forward position; Section 5 contains the empirical work; Section 6 provides conclusions.

2. Market Risk Assessment

In general, the procedure for calculating risk in banking begins with a calculation of the market value of the positions and continues with an estimation of the future value of the positions as a result of estimation of changes in rates and prices. As defined in the introductory chapter, risk is the probability associated with the value of banks in the future. Therefore, to calculate the market risk of banks we need to: (1) calculate the value of the current positions (as defined above); and (2) estimate the value of the positions in the future (next day, next week, or at some point in the future). This study will adopt this procedure to calculate banks' market risks.

There are a variety of approaches to calculating market risk. In general, we can distinguish two categories: the regulatory approach and alternative approaches. Banks normally use both categories. The adoption of the regulatory approach is necessary to comply with regulation and the adoption of an alternative approach (i.e. internal models) is necessary to manage risk in an optimal way. In fact, the regulatory authorities usually allow banks to use alternative methods to calculate minimum capital adequacy requirements with respect to market risk under certain guidelines. For these reasons, this study will embrace both regulatory and alternative methods. The following sub-section discusses VaR, which is as an alternative model for assessing bank risk.

3. Models

The main objective of this section is to design new models for market risk. Discussion begins with the theoretical overview of market risk and the standardised method of capital adequacy regulation from regulatory authorities Bank for International Settlement (BIS). This study suggests new models based on theories in finance and econometric and then, gives examples of application those models in a position of a foreign exchange forward buying

3.1. Theory Of Market Risks

$$VaR_{t+1} = V_t s_{t+1} \quad (1)$$

where

VaR_{t+1} = value at risk

V_t = market value of positions at time" t " (risk exposure)

s_{t+1} = volatility of risk factors at time " $t+1$ "

3.2. BIS Standardised Method (BIS, 1996)

The standardised method adopts the following approach:

- V is marked to market only for trading book
- s is determined based on consensus between member countries (ie. 8% for foreign exchange risk)
- Over all risk equals to the summation of risk of an individual position (ie. ignoring risk correlation). This approach violates the portfolio theory (see Sharp, 1970 , pp.34-44)

Details of criticisms for the standardised method have been discussed in Hall (1994)

3.3. Suggested Models

This study suggests that marked to market for V can be extended to fixed incomes and over the counter (OTC) derivatives using the following models:

$$V_t = C_{t+k} \frac{1}{(1+i)^k} \quad (2)$$

where,

C_t = cash flow at time " t "

i = yield to maturity (ie. we assume that the spot rate is the same as the yield of zero coupon bond)

k = period from at the time the risk is assessed (" t ") to " $t+k$ "

This study also suggests that the volatility of a risk factor at time "$t+1$" (s_{t+k}) such as exchange rates, stock price, interest rates, and commodities can be estimated using time series forecasting techniques.

Daily value at risk of the "n" instrument at time "t" can be shown in the following equation:

$$DaR_{n|t} = V_{n|t} s_{n|t+1}$$

where,

"$t+1$" is the day after "t" (ie. the day when the risk is assessed)

$s_{n|t+1}$ = the daily price risk for the instrument "n"

This study adopts the price volatility rather than yield volatility[2]. Assuming that "i" yield in currency (r) will be delivered at time "$t+k$", the price risk (P_k) of one unit currency (r) at yield "i" and for period "$t+k$" is the following equation:

$$P_k = i_r \left[\frac{1}{(1+i_r)^k} \right] \qquad (3)$$

where,

P_k = the price of "k" period zero coupon bond denominated in currency "r"

i = the spot rates of zero coupon bond in currency "r" for "k" period ahead.

k = the time when the cash flow is received

The price volatility of "k" period zero coupon bond can be derived from the following equation:

$$s_{pk} = s_i P_k \qquad (4)$$

where,

s_{pk} = the price volatility of "k" period zero coupon bond

s_r = the daily yield volatility of "k" period zero coupon bond in currency "r"

Diversified daily value at risk (DDaR) can be derived from the following equation:

$$DDaR_{nj} = \sqrt{(DaR_n)^2 * (DaR_j)^2 + 2 * r_{nj} * DaR_n * DaR_j} \qquad (5)$$

where,

$DDaR_{nj}$ = Diversified daily value at risk for instrument "n" and "j"

DaR_n = Daily value at risk for instrument "n"

DaR_j = Daily value at risk for instrument "j"

2 Price volatility is normally used for fixed income valuations when the price of an instrument is not a linear one to one to the yield.

ρ_{nj} = Risk correlation between risk factor in instrument "n" and "j"

3.4. Treatment For Option Positions

To assess risks of non-linear positions (ie. options), this study will employ the second order of Taylor series expansion around the spot rates. Assuming that the price of an option depends on several risk factors such as the strike price (K), spot price of underlying instrument (P), time to maturity (t), risk-less of interest rates (r), and volatility of the price of underlying instrument (σ), the value of options can be calculated in the following equation:

$$V(P,K,t,r,\sigma) \cong V_0(P,K,t,r,\sigma) + \left.\frac{\partial V}{\partial P}\right|_{V_0}(K-P_0) + \frac{1}{2}\left.\frac{\partial^2 V}{\partial P^2}\right|_{V_0}(K-P_0)^2 + \ldots\ldots\ldots + \left.\frac{\partial V}{\partial \sigma}\right|_{V_0}(\sigma-\sigma_0) + \frac{1}{2}\left.\frac{\partial^2 V}{\partial \sigma^2}\right|_{V_0}(\sigma-\sigma_0)^2 \quad (6)$$

where,

V = the estimated value of option

V_0 = the value of options at time "t_0"

The DaR of options depends on the volatility of the risk factors which can be estimated using forecasting techniques. Diversified risk in option can be solved by employing correlation of underlying factors (ie. P,K,t,r,σ). Normally we call these as Greek letters.

4. Application The Models Of Market Risks To Foreign Exchange Forward Positions

The standardised method assumes that risk exposure of foreign exchange forward positions (FxFwd) is the summation of a long position of nominal amount in buying currency and a short position of nominal amount in selling currency. Risk of each positions is assessed by employing an 8% risk weight.

Actually, the FxFwd is the exchange of buying currency and selling currency in the future with a certain exchange rate. These positions can be mapped in similar approach as those in the fixed incomes:

1. Receiving of buying currency (C_b) at point in time in the future (ie. one year to come)
2. Delivering of selling currency (C_s) at the same time as that in point number one.

Based on those cash flows, C_b is sensitive to a price volatility of buying currency (s_b) and C_s is sensitive to a price volatility of selling currency (s_s). Finally, we can calculate DaR for C_b and C_s and diversified portfolio (ie. $DDaR_{bs}$).

However, the selling currency is also sensitive to the price of foreign exchange forward (s_f). In forward buying, the amount of selling and buying currency will be fixed as mentioned in the contract. However, the price in the market at the delivery date is probably higher or lower than that in the contract. If it is the case, seller may get benefit and the other will suffer loss. Therefore, we need to incorporate the forward price into risk exposure of selling currency.

Assuming:

i_b is the yield of buying currency

i_s is the yield of selling currency

s_{yb} is the daily yield volatility of buying currency

s_{ys} is the daily yield volatility of selling currency

s_f is the price volatility of forward rates

The risk of FxFwd is the following:

$$V_b = C_b \left[\frac{1}{(1 + i_b)^1} \right]$$

$$C_s = C_b * Forward\ rates$$

$$V_s = C_s \left[\frac{1}{(1 + i_s)^1} \right]$$

$$s_b = s_{yb} i_b \left[\frac{1}{(1 + i_b)^1} \right]$$

$$s_s = s_{ys} i_s \left[\frac{1}{(1 + i)^1} \right]$$

$$DaR_b = V_b s_b$$

$$DaR_s = V_s s_s$$

$$DaR_f = V_s s_f$$

$DDaR$ can be solved by using equation number 5.

These models also can be applied to positions of bonds, forward rate agreement and swaps by mapping those positions based on expected cash flows.

5. Empirical Works

This study conducts an empirical work to compare the foreign exchange risk estimates using standardised method and the alternative models as have been discussed in the previous sections. This empirical work will employ foreign exchange exposure of one of Indonesian banks. The focus of this empirical work is to estimate the volatility and correlation of IDR exchange rates and applies the results to assess foreign exchange risk of spot positions in a sample bank. Finally, this study adopts the following procedures: (1) Estimate the volatility (s) and correlation (r) of IDR exchange rates using GARCH; (2) Employing risk and correlation estimates into alternative models to assess foreign exchange risk; (3) Employing foreign exchange risk using standardised method; (4) Compare capital requirement for foreign exchange risk estimated from standardised method and alternative models.

5.1. Data

This study employs daily spot exchange rate returns of 18 IDR exchange rates which are going to be used to asses foreign exchange risk of a sample bank. Exchange rate returns in this study are derived from the following formula:

$$r_t = (LnR_{t+1} - LnR_t)\, x\, 100\% \qquad (7)$$

where r_t is an exchange rate return at time "t" and R_t is the exchange rate at time "t".

The exchange rate data is derived from the mid prices of a commercial bank in Indonesia. The ownership of this bank is a joint between government and public. Therefore, we believe that the exchange rate policy of this bank is independent.

5.2. Estimating Volatility Using GARCH

5.2.1. Mean Process

It is also possible that a time series is generated from combination between AR and MA models (Box-Jenkin, 1976). To get a stationary time series, some time we need to differentiate the series to get an integrated time series before employing the series into models. Box-Jenkin identify this model as Autoregressive Integrated Moving Average (ARIMA). The following discussion contains the mathematical background of this model.

Assuming the first difference of integrated time series is $y_1, y_2, \ldots\ldots\ldots\ldots\ldots y_t$. The ARIMA (p,1,q) models can be shown in the following equation:

$$y_t = f_1 y_{t-1} + \ldots\ldots\ldots\ldots + f_p y_{t-p} + e_t - q_1 e_{t-1} - \ldots\ldots\ldots q e_{t-q} \qquad (8)$$

Appendix 6 shows how to solve the f and q mathematically.

5.2.2. Variance Process

In forecasting, normally we assume that the variance of disturbance term (s^2) is constant over time "t". However, the actual volatility of a time series is not always constant. Engle (1982) introduced a forecasting method by allowing the variances vary over time. This model is called Autoregressive Conditional Heteroscedasticity (ARCH). These models have been widely used in economics and finance (see Engle , 1987; Engle, 1991; French, 1987; Nelson, 1990)

Based on the identification process, we may conclude that time series were generated from a particular process such as AR, MA or combination AR and MA (ie. ARMA). It is also possible that time series are integrated either at level or after the first difference. To simplify the discussion below, we assume that the mean process is ARMA(1,1). To forecast foreign exchange rate return "y" at time "t" using ARM A(1,1) is in the following equation:

$$y_t = a_1 y_{t-1} + e_t + b_1 e_{t-1} \qquad (9)$$

Where,

y_t = the exchange rate return at time "t"

a_1 = the slope

e_t = the residual

b = the coefficient of MA process

To forecast the variance at time "$t+1$" (e_{t+1}^2) we can employ the following method:

$$\text{Var}\,(y_{t+1}|y_t) = E_t[(y_{t+1} - b_1 e_{t-1} - a_1 y_t)^2]$$
$$= E_t e_{t+1}^2$$

The ARMA process assumes that the variance is constant over time. In mathematical term, this assumption is in the following equation:

$$E_t e_{t+1}^2 = E_t e_t^2 = E_t e_{t-1}^2 = \ldots\ldots\ldots E_t e_{t-p}^2 = s^2$$

However, many researchers who involve in forecasting financial time series (ie. stock prices, inflation rates, foreign exchange rates, interest rates, etc) have observed that the forecast errors vary over time.

Assuming that the variance is conditional to the past variances or the variance is not constant. In mathematical expression is in the following equation:

$$\hat{e}_t^2 = a_0 + a_1 \hat{e}_{t-1}^2 + a_2 \hat{e}_{t-2}^2 + \ldots\ldots\ldots\ldots + a_q \hat{e}_{t-q} + v_t$$

Where, v_t is a white-noise process (ie. zero mean, $v_t v_t (s_v^2) = 1$ and $v_t v_{t-1} = 0$)

Engle (1982) employs multiplication form of conditional heteroscedasticity model with order 1 as shown in the following:

$$e_t = v_t \sqrt{a_0 + a_1 e_{t-1}^2} \qquad (10)$$

Where v_t is white noise process.

Other constraints are required for equation number 10 such that a_0 and a_1 are constant, $a_0 > 0$ and $0 < a_1 < 1$, and $v_t e_{t-1} = 0$ in order to maintain the stability of autoregressive process.
The ARCH of variance process may follow a "q" order which can be shown in the following equation:

$$s_t^2 = v_t^2(a_0 + \sum_{i=1}^{q} a_1 e_{t-1}^2)$$

$$e_t = \sqrt{a_0 + \sum_{i=1}^{q} a_1 e_{t-1}^2} \qquad (11)$$

The equation above is the same as a model of time-varying parameter with MA(q).

Bollerslev (1986) expands the Engle's work by considering AR process in the heterocedasticity of variances into generalise autoregressive heterocedasticity (GARCH). In mathematical expression, GARCH can be shown in the following equation:

$$s_t^2 = v_t^2\left(a_0 + \sum_{i=1}^{q} a_i e_{t-1}^2 + \sum_{i=1}^{p} b_i s_{t-1}^2\right) \qquad (12)$$

where,

MA (q) process of residuals is $\sum_{i=1}^{q} a_i e_{t-i}^2 = a_1 e_{t-1}^2 + a_2 e_{t-2}^2 + ... + a_q e_{t-q}^2$

AR(p) process of variances is $\sum_{i=1}^{p} b_i s_{t-1}^2 = b_1 s_1^2 + b_2 s_2^2 + ... + b_p s_{t-p}^2$

since v_t^2 =1 and $s_t^2 = \left(a_0 + \sum_{i=1}^{q} a_i e_{t-1}^2 + \sum_{i=1}^{p} b_i s_{t-1}^2\right)$

When the variances (s_t^2) are heterocedastic, we can replace the symbol s_t^2 with h_t (ie. heterocedasticity).

To test time variant in variances, this study employs LM test on the ARMA variances. This method has been used widely by authors to test the autocorrelation of variances (see Breusch and Pagan, 1978, 1980, Godfrey, 1978 and Engle, 1982).

5.3. Exponential weighted moving average (EWMA)

The main discussion in this chapter covers the theories of EWMA and the choice of the decay factor by J.P. Morgan. The aim of this section is to examine whether the decay factor suggested by J.P. Morgan is valid for IDR exchange rate volatility.

5.3.1. Theory of EWMA

This method was developed for the first time in the late 1950s by operations research personnel. The many sources available make it difficult to decide who discovered the smoothing methods. Cox (1961) indicates that either Holt (1957) or Brown (1956) used the exponential smoothing method for the first time. Muth (1960, p.299) suggests that J.F. Magee (1958) was the first person to use the smoothing techniques. Most of the important works which employed exponential smoothing were done in the late 1950s and published in the 1960s and the dates of the publications are unreliable in helping to identify who first used the exponential-smoothing techniques. Many other authors also used the smoothing techniques after the 1960s, for example Holt *et al* (1960), Winters (1960), Brown and Meyer (1961), Nerlove and Wage (1964), Theil and Wage (1964), and J.P. Morgan (1995). Most of the previous works only used EWMA in marketing and productions. They concluded that the models predict quite well. By estimating tourist demand in Hawaii, Geurts (1975) claims that the exponential smoothing model is outperformed by the Box-Jenkins (i.e. ARIMA models) approach. The following discussion provides the theoretical background to the EWMA.

In EWMA, the next estimated observation of a time series (F_{t+1}) is a function of the previous forecast (F_t) and the observation (X_t) at time "t" (Brown, 1963; Cox, 1961; Winters, 1960). In mathematical terms, we can express this in the following equations:

Model 1:

$$F_{t+1|t} = aF_{t|t-1} + (1-a)X_t \tag{13}$$

where,

a = the decay factor with a constraint of 0< a <1,

F_{t+1} = the forecast of variance at time "$t+1$"

X_t = the observation (i.e. sample variance) at time "t"

We can rearrange equation 13 by replacing the definition of F_t and substituting for $(1-a) = r$ in the following equation:

$$F_{t+1|t} = a\,(aF_{t-1|t-2} + rX_{t-1}) + rX_t$$
$$= a^2 F_{t-1|t-2} + arX_{t-1} + rX_t$$
$$= a^2 (aF_{t-2|t-3} + rX_{t-2}) + arX_{t-1} + rX_t$$
$$= a^3 F_{t-2|t-3} + a^2 rX_{t-2} + arX_{t-1} + rX_t$$

Assuming that the initial forecast is the same as the first observation ($T = 1 + q$), we can rearrange the forecast equation into the following:

$$F_{t+1|t} = a^q rX_{t-q} + a^{q-1} rX_{t-(q-1)} + \ldots\ldots a^3 rX_{t-3} + a^2 rX_{t-2} + arX_{t-1} + rX_t$$

$$F_{t+1|t} = r\sum_{i=0}^{q} a^i X_{t-i} \qquad (14)$$

Additionally, model 2 can be applied:

Model 2:

$$F_{t+1|t} = aX_t + (1-a)F_{t|t-1}$$

The value of a plays an important role in EWMA. If the value of a equals a figure which is close to 1, this forecast will adopt a small adjustment for the errors in the previous forecast. On the other hand, if the value of a is close to 0, the model gives substantial adjustment of the previous errors. Without any rule to decide the value of a, we can select the value of a to get the intended results of forecasting.

Indicators to decide the value of a are required, to ensure that there is no subjective treatment in forecasting. This study will employ root mean square errors (RMSE) as an indicator to decide the value of a. Using time series data, the best value of a is derived from the value which gives the minimum RMSE. This study will adopt a trial and error method to chose the RMSE.

The next issue for EWMA is to determine the initial value of the forecast (i.e. F_0). For a small T and when a is close to 1, the initial value plays a crucial part in forecasting. However, since the time “T” is large enough and the a is close to 0, the initial value of the forecast (F_0) does not affect the outcome of the forecasts too much. Box-Jenkins (1976, pp.199-200) adopt back-forecasting which can be applied to the exponential smoothing method. The method simply inverts the time series data and starts the estimation from the most recent series and moves to the oldest one. Because our observations are numerous (350 observations), the initial value of forecasting will not affect the results too much. Therefore, this study assumes that the F_0 equals 0.

5.3.2. Universal Optimum Decay Factor in EWMA

J.P. Morgan (1996) suggests that the decay factor of 0.94 is valid to forecast the daily volatility and correlation for all instruments. A universal decay factor is adopted as a practical applications by users. The universal decay factor is derived from a weighted average of individual optimal decay factors. The weight represents the individual forecast accuracy. The following discussion shows how the universal decay factor is derived.

Assuming that $\hat{l}_i$ represents the optimal decay factor for instrument i, $N(i = 1,2\ldots\ldots3)$ stands for the number of time series included in forecasting, and t_i is the minimum RMSE for the time series i. Based on the J.P. Morgan approach, the universal decay factor can be derived from the following procedures:

- calculate the sum of t_i using the following equation:

$$\Pi = \sum_{i=1}^{N} t_i$$

- define the relative error using the following equation:

$$q_i = \frac{t_i}{\sum_{i=1}^{N} t_i}$$

- define the weight using the following equation:

$$f_i = \frac{q_i^{-1}}{\sum_{i=1}^{N} q_i^{-1}}$$

where $\sum_{i=1}^{N} f_i = 1$

- the optimal decay factor , $\hat{l}$ is defined in as the following equation:

$$\overline{l_i} = \sum_{i=1}^{N} f_i \hat{l_i}$$

Using 480 time series, J.P. Morgan finds that the optimum decay factor is 0.94, which is believed to be valid for all currencies. The decay factor is derived from the series which comprises of foreign exchange rates, 5 year swaps, 10-year zero coupon bond prices, equity indices, and 1-year money market rates. However, the purpose of the universal decay factor is just to simplify the calculation of risk assessment for users. From the discussion above, we can conclude that the approach assigns the higher weight for the lower RMSE.

I we apply the methodology on 18 IDR exchange rates, the optimum decay factor is 0.98. The decay factor on USD/IDR exchange rate returns contributes significantly to the optimum decay factor because the RMSE on USD/IDR exchange rate returns is lower than the others. The results provide evidence that the decay factor of 0.94 is not valid for IDR exchange rate returns.

The next sub-section shows the empirical study of forecasting IDR using EWMA. The aim of this empirical work is to find whether forecasting using the original decay factor yields different results.

5.4. Empirical Results

5.4.1. Using GARCH

Before employing data into models, this study adopts the Dickey-Fuller (1979) test to examine the stationary of the data. Additionally, this study also adopts Box-Pierce (1970) and Ljung-Box (1978) to test white-noise process of data. Based on those tests, IDR exchange rate returns are generated from stationary and white-noise process. Therefore, the data of IDR exchange rate returns are eligible to be used in forecasting using GARCH models.

Using TSP window version (EVIEWS) software package, this study discovers that 11 series have zero means and 7 series have non-zero means. All series are generated from ARCH process while only 6 series are generated from GARCH process. Details of the models are in the following table:

Table 1
Means and Heteroscedasticity Process of Variance Models

No.	Currency	Mean Process	Conditional Variance
1	ATS	$y_t = 0 + e_t$	$h_t = 0.21 + 0.17e^2_{t-1}$
2	AUD	$y_t = 0 + e_t$	$h_t = 0.14 + 0.13e^2_{t-1}$
3	BEF	$y_t = 0 + e_t$	$h_t = 0.10 + 0.04e^2_{t-1} + 0.65s^2_{t-1}$
4	BND	$y_t = 0 + e_t$	$h_t = 0.13 + 0.28e^2_{t-1}$
5	CAD	$y_t = 0 + e_t$	$h_t = 0.31 + 0.26e^2_{t-1}$
6	CHF	$y_t = 0 + e_t$	$h_t = 0.35 + 0.14e^2_{t-1}$
7	DEM	$y_t = 0 + e_t$	$h_t = 0.28 + 0.21e^2_{t-1}$
8	DKK	$y_t = 0 + e_t$	$h_t = 0.21 + 0.15e^2_{t-1}$
9	FFR	$y_t = -0.57y_{t-1} + e_t$	$h_t = 0.06 + 0.13e^2_{t-1} + 0.71s^2_{t-1}$
10	GBP	$y_t = 0 + e_t$	$h_t = 0.06 + 0.14e^2_{t-1} + 0.59e^2_{t-1}$
11	HKD	$y_t = 0.02 + e_t$	$h_t = 0.03 + 0.24e^2_{t-1}$
12	ITL	$y_t = -0.14y_{t-1} + e_t$	$h_t = 0.02 + 0.11e^2_{t-1} + 0.84e^2_{t-1}$
13	JPY	$y_t = 0 + e_t$	$h_t = 0.11 + 0.26e^2_{t-1} + 0.41s^2_{t-1}$
14	MYR	$y_t = 0.03 - 0.16y_{t-1} + e_t$	$h_t = 0.03 + 0.58e^2_{t-1}$
15	NLG	$y_t = -0.23y_{t-1} + 0.11e_{t-2} + e_t$	$h_t = 0.25 + 0.54e^2_{t-1}$
16	NZD	$y_t = -0.18y_{t-1} + e_t$	$h_t = 0.01 + 0.11e^2_{t-1} + 0.85s^2_{t-1}$
17	SEK	$y_t = 0 + e_t$	$h_t = 0.23 + 0.15e^2_{t-1}$
18	USD	$y_t = 0.02 - 0.34y_{t-1} + e_t$	$h_t = 0.00 + 0.23e^2_{t-1}$

Using those models, we estimate the IDR negative returns for the next day (ie. 2 June 1997) by employing one tail of a 2.5% confidence level with the assumption that the IDR exchange rate returns are normally distributed from their. In mathematical terms, the estimates are calculated from the following equation:

$$\hat{y}_t = \bar{y}_t + 1.96s_t \qquad (15)$$

The estimates on 2 June 1997 are the following:

Table 2
IDR Exchange Rate Returns: Estimates on 2 June 1997

Currency	Variances	Standard deviation	Conditional Mean	Estimates
ATS	0.32	0.56	0.00	-1.11
AUD	0.16	0.39	0.00	-0.77
BEF	0.28	0.53	0.00	-1.04
BND	0.14	0.37	0.00	-0.72
CAD	0.31	0.56	0.00	-1.09
CHF	0.51	0.72	0.00	-1.40
DEM	0.36	0.60	0.00	-1.18
DKK	0.29	0.54	0.00	-1.05
FRF	0.29	0.54	-0.29	-1.35
GBP	0.18	0.42	0.00	-0.82
HKD	0.51	0.71	0.02	-1.38
ITL	0.28	0.53	0.09	-0.95
JPY	0.22	0.47	0.00	-0.91
MYR	0.03	0.18	0.03	-0.32
NLG	0.46	0.68	0.14	-1.18
NZD	0.18	0.43	0.13	-0.71
SEK	0.24	0.49	0.00	-0.96
USD	0.00	0.03	0.02	-0.04

All estimates of negative exchange rate returns are less than 8% which is the figure suggested by Bank Supervision Committee, BIS on standardised method.

This section will employ the estimates of IDR negative returns to foreign exchange exposure of a sample bank in Indonesia to asses its foreign exchange risk and compare the results to the those in the standardised method of BIS proposals. This section also assesses the difference between the daily risk (DaR) and daily diversified risk (DDaR) in foreign exchange portfolio positions. According to the risk diversification theory (see Sharp, 1970), the volatility of one currency may affect to the volatility of other currencies. The risk which considers the volatility correlation with other currencies is called DDaR in this study.

Volatility correlation is derived from the following formula:

$$r_{ij,t} = \frac{h_{ij,t}}{\sqrt{h_{it}^2} * \sqrt{h_{jt}^2}} \quad (16)$$

where,

$r_{ij,t}$ = the volatility correlation of the variances on IDR exchange returns in currency i and currency j at time t

$h_{ij,t}$ = the covariance of the IDR exchange rate returns in currency i and currency j at time t.

The results of risk assessment using one tail of a 2.5% confidence level are in the following table:

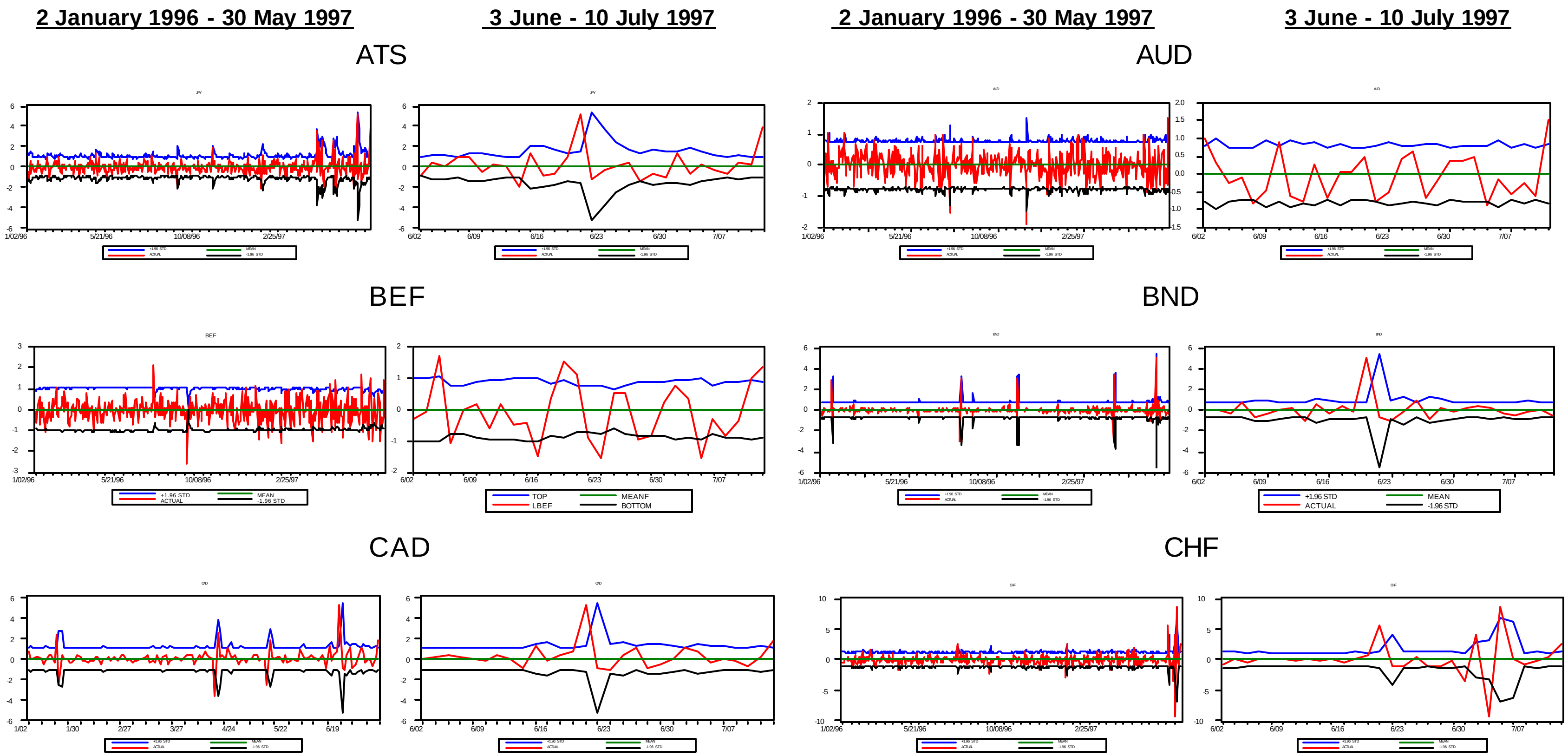
Table 3
FX Risk of a Sample Bank using GARCH

1=IDR 1,000

Currencies	Net Position	GARCH estimates	DaR using GARCH
ATS	1,236,858	-1.106	(13,675)
AUD	6,107,616	-0.773	(47,233)
BEF	488	-1.045	(5)
BND	23,934	-0.723	(173)
CAD	334,553	-1.095	(3,662)
CHF	1,532,204	-1.404	(21,505)
DEM	6,422,919	-1.175	(75,499)
DKK	425,981	-1.050	(4,475)
FFR	1,799,277	-1.346	(24,214)
GBP	34,886,948	-0.823	(287,086)
HKD	9,021,071	-1.381	(124,592)
ITL	77,882,972	-0.950	(740,132)
JPY	3,790,421,766	-0.913	(34,608,476)
MYR	14,996,934	-0.323	(48,367)
NLG	1,219,866	-1.184	(14,446)
NZD	240,219	-0.705	(1,695)
SEK	320,558	-0.963	(3,087)

Currencies	Net Position	GARCH estimates	DaR using GARCH
USD	643,608,560	-0.039	(249,649)
Daily at Risk (DaR)			(36,267,970)
Diversified Daily at Risk (DDaR)			(34,958,455)

Graph 1.A
Plot of GARCH Estimates Using a 5% Confidence Level

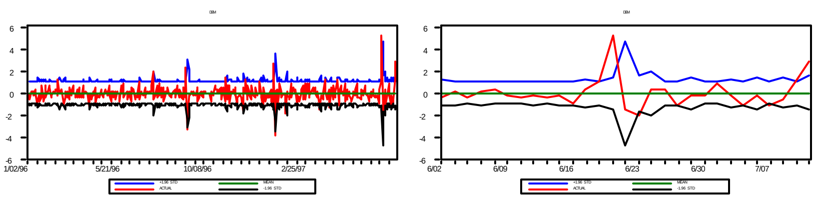


Graph 1.B

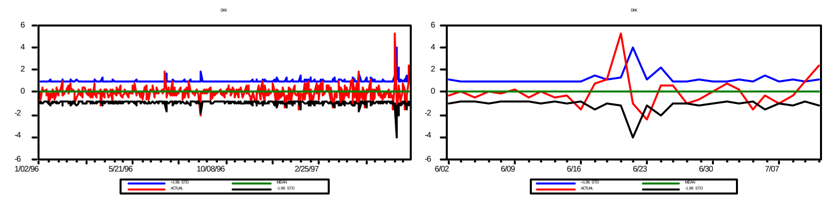
Plot of GARCH Estimates Using a 5% Confidence Level

2 January 1996 - 30 May 1997 | **3 June - 10 July 1997** | **2 January 1996 - 30 May 1997** | **3 June - 10 July 1997**

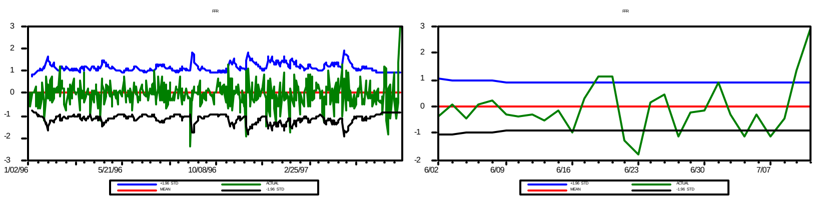
DEM



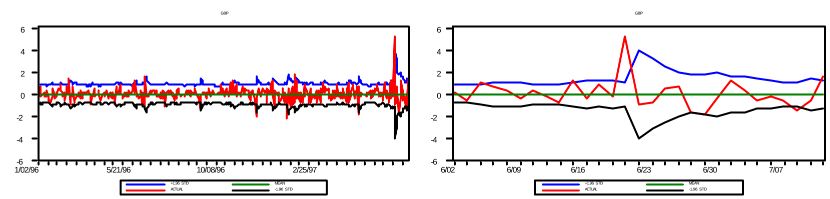
DKK



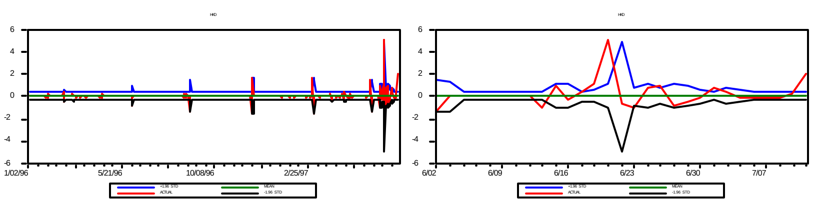
FFR



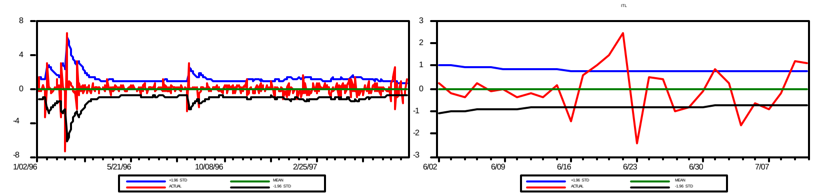
GBP



HKD



ITL

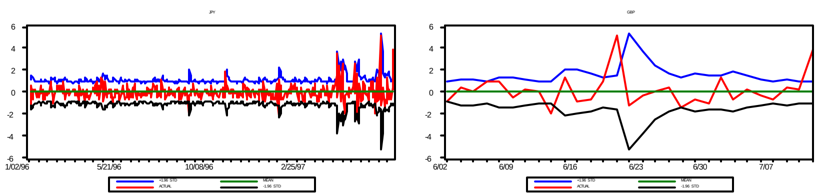


Graph 1.C

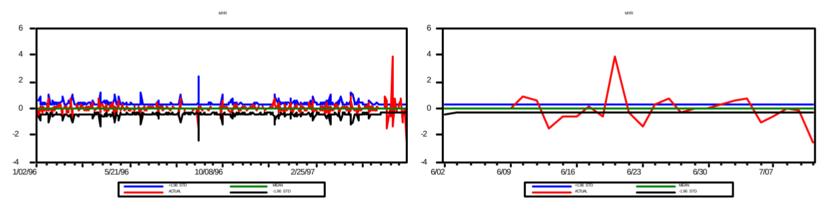
Plot of GARCH Estimates Using a 5% Confidence Level

2 January 1996 - 30 May 1997	3 June - 10 July 1997	2 January 1996 - 30 May 1997	3 June - 10 July 1997

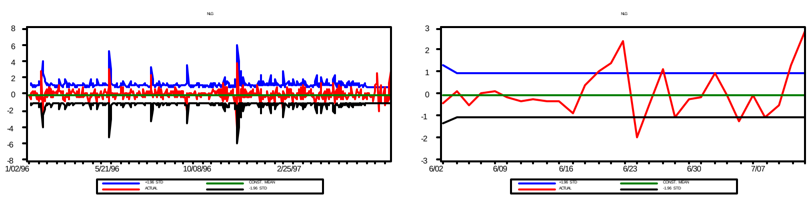
JPY



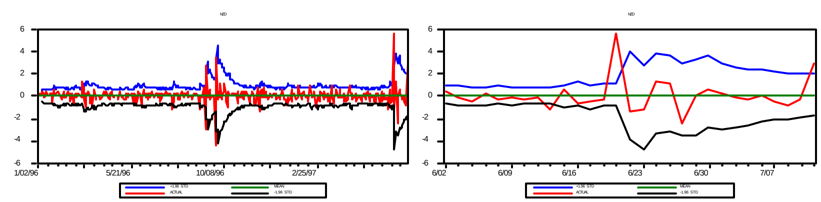
MYR



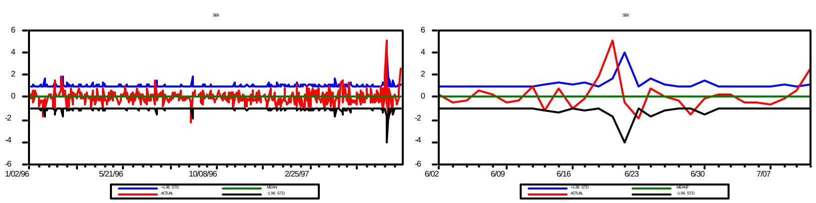
NLG



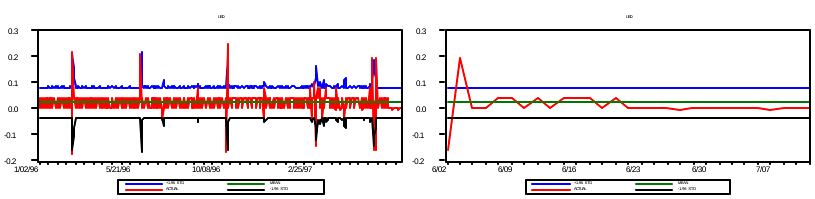
NZD



SEK



USD



5.4.2. Using EWMA

By employing RMSE , the decay factors (DFs) of IDR exchange rate returns are shown in the following Table:

Table 4

Decay Factors (a) of IDR Exchange Rate Returns

No.	Currencies	a for model 1: $\left[F_t = aF_{T-1} + (1-a)X_{t-1}\right]$	a for model 2 : $\left[F_t = aX_{t-1} + (1-a)F_{t-1}\right]$
1	**ATS**	0.989	0.011
2	**AUD**	0.967	0.033
3	**BEF**	1.000	0.000
4	**BND**	0.987	0.013
5	**CAN**	0.967	0.033
6	**CHF**	0.968	0.032
7	**DEM**	0.997	0.003
8	**DKK**	0.995	0.005
9	**FFR**	0.994	0.006
10	**GBP**	0.935	0.065
11	**HKD**	0.994	0.006
12	**ITL**	0.942	0.058
13	**JPY**	0.945	0.055
14	**MYR**	0.967	0.033
15	**NLG**	0.994	0.006
16	**NZD**	0.987	0.013
17	**SEK**	0.980	0.020
18	**USD**	0.975	0.025

The coefficients of a are near 0 in model 1 and near to 1 in model 2. These results support the findings that the series are whitenoise. Since the time series data is generated from a whitenoise process, GARCH will provide more accurate estimates than EWMA. Lawrence and Robinson (1995) and West and Cho (1995) also support this finding. However, EWMA is more simple, practical and suitable for most users (Longerstaey and Zangari, 1995). They argue that EWMA can provide similar volatility with GARCH (1,1). However, the empirical results suggest that this argument is invalid for IDR exchange rate returns.

Table 5 shows the DDaR of foreign exchange position of the sample bank calculated using EWMA with original and J.P. Morgan's decay factors.

Table 5
DDaR Estimates Using EWMA

	Net Position	Volatility(%) using original DF	DaR using original DF	Volaltility (%) usingn a 0.94 DF	DaR using a 0.94 DF
ATS	1,236,857.82	-1.11	(13,773.95)	-1.04	(12,903.44)
AUD	6,107,616.04	-0.85	(52,185.92)	-0.61	(37,539.12)
BEF	488.25	-1.12	(5.49)	-0.96	(4.68)
BND	23,934.40	-0.92	(221.34)	-0.83	(197.47)
CAD	334,552.68	-1.34	(4,477.02)	-1.39	(4,641.19)
CHF	1,532,203.80	-1.37	(20,943.65)	-1.21	(18,535.68)
DEM	6,422,919.14	-1.13	(72,824.09)	-0.95	(61,303.30)
DKK	425,981.25	-1.21	(5,158.97)	-1.15	(4,904.38)
FFR	1,799,277.12	-1.05	(18,831.83)	-0.92	(16,534.42)
GBP	34,886,947.65	-0.94	(327,615.84)	-0.88	(308,701.69)
HKD	9,021,070.80	-0.52	(46,772.53)	-0.72	(65,239.71)
ITL	77,882,972.44	-0.91	(708,784.39)	-0.97	(753,722.13)
JPY	3,790,421,766.15	-1.91	(72,470,620.58)	-1.90	(72,126,065.90)
MYR	14,996,934.42	-0.43	(64,653.94)	-0.37	(55,741.74)
NLG	1,219,865.56	-1.20	(14,618.11)	-0.98	(11,966.32)
NZD	240,219.00	-0.69	(1,658.38)	-0.68	(1,625.25)
SEK	320,557.77	-1.09	(3,496.05)	-1.03	(3,315.73)
USD	643,608,560.00	-0.10	(627,846.30)	-0.13	(826,493.34)
Daily at risk (DaR)			(74,454,488.38)		(74,309,435.48)
Diversified daily at risk (DDaR)			72,793,852.50		72,437,750.09

The results show that the original decay factor yields a higher risk than the J.P. Morgan approach (i.e. using a 0.94 decay factor).

The following section discusses estimation models using GARCH, and conducts an empirical study to estimate the IDR exchange rate returns. The aim of this empirical study is to prove that a decay factor approaching 1 is one piece of evidence that the series is whitenoice, and, therefore, that the GARCH model provides more accurate estimates.

5.4.3. Comparison of Standardised Methodology, EWMA and GARCH

Risk assessment on foreign exchange using standardised method is in the following table:

Table 6

Foreign Exchange Risk Using the BIS Standardised Method

Currency	Long	Short	Net Position	Short position
USD	8,373,301,640	(7,729,693,080)	643,608,560	
ATS	87,546,688	(86,309,830)	1,236,858	
AUD	7,400,184	(1,292,568)	6,107,616	
BEF	1,573,909	(1,574,397)		(488)
BND	23,934	0	23,934	
CAD	132,759	(467,312)		(334,553)
CHF	12,582,382	(11,050,178)	1,532,204	
DEM	116,792,616	(110,369,697)	6,422,919	
DKK	425,981	0	425,981	
FFR	9,164,324	(7,365,047)	1,799,277	
GBP	82,776,884	(47,889,937)	34,886,948	
HKD	(8,442,627)	(578,444)		(9,021,071)
ITL	180,971,516	(103,088,543)	77,882,972	
JPY	11,618,610,327	(7,828,188,561)	3,790,421,766	
MYR	18,692,184	(33,689,118)		(14,996,934)
NLG	3,047,112	(1,827,246)	1,219,866	
NZD	324,997	(4,439)	320,558	
SEK	241,521	(1,302)	240,219	
Sum			4,566,129,678	(24,353,046)
Foreign exchange risk 8% from			365,290,374	

The results show that the GARCH models suggest lower capital requirements are required than suggested by either the standardised method or EWMA[i.e. the standardised method requires IDR 365,290,374 thousand, EWMA with original decay factors requires IDR 72,793,852 thousand, EWMA with a 0.94 decay factor requires IDR 72,437,750 thousand, while GARCH only requires IDR 34,958,455 thousand]. To cover shock events, the BIS proposal (1996) requires banks which use internal models to multiply the results by a certain multiplication factor (not less than 3). Assuming we use a multiplication factor of 3, the GARCH results show that required capital should still be far below that suggested by the standardised method - see the calculation below.

Table 6
Comparison of Risk Using GARCH and the BIS Standardised Method

Models	Risk	After multiplying by 3	The difference from the standardised method
GARCH	34,958,455	104,875,365	365,290,374-104,875,365 =260,415,009
EWMA	72,793,852	228,908,818	365,290,374 – 218,381,556 =146,908,818
BIS	365,290,374		

Finally, we can thus conclude that the GARCH models suggest a lower capital requirement than that applicable under the standardised methodology. This finding is consistent with the results of the empirical study by Jackson *et al* (1997). He found that the actual losses are lower than the results generated by multiplying daily risk by 2.5.

6. Conclusions Of Market Risk Assessment

The decay factors of IDR exchange rates for EWMA vary. This finding contradicts the assertion of JP. Morgan that the 0.94 decay factor is universal, even for interest rate risk (J.P. Morgan, 1995, 1996). Adoption of a universal decay factor will thus be misleading for risk assessment. However, Longerstaey and Zangari (1995) argue that Riskmetrics' methodology is the best way of resolving the dispute between theory and practice.

The results of the GARCH estimates are different from those of EWMA. This finding therefore contradicts the suggestion that EWMA estimates are similar to GARCH (1,1). Additionally, it has been shown the GARCH models can provide a lower error of estimates than EWMA .

The 8% risk weighting for all currencies in the BIS standardised methodology is higher than suggested by the GARCH estimates. This finding thus provides evidence that the standardised methodology is misleading as a guideline for assessing exchange rate risk. This finding also provides information for the Indonesian government (i.e. the central bank of Indonesia) on how to select the appropriate multiplication factors to capture shock events. Adoption of a multiplication factor of 3 (as required in the BIS proposal of 1996) still gives much lower results than the standardised method since the highest estimated negative returns are only 1.40% (for CHF) in GARCH.

The GARCH approach however may result in different estimates being provided by each forecaster. In an extreme case, two econometricians may produce different estimates for the same data. This constraint leads to the adoption of different GARCH processes in banks, and demands a detailed verification of each model before a central bank allows the models to be used within risk assessment for capital adequacy purposes.

The regulatory authorities should be aware of the arbitrary results in the GARCH models. Stahl (1997) reported that internal models may face errors because modelling normally simplifies the real world, using approximations in the calculation and testing the models using samples which represent the population. One of the possible solutions to this issue is to examine thoroughly the internal models of each bank before granting approval for its usage. This treatment, however, may cause heated debate between banks and the authorities and will be time consuming. The regulatory authorities may thus decide to adopt the same GARCH process for all time series data for banks which are interested in using GARCH models in forecasting volatility under certain requirements. This approach will be fair to all banks.

The pre-commitment approach may also be applicable (Federal Reserve Board, 1995)[3]. However, this method is less prudent when the banks set the pre-commitment level of capital far below that required by true level of risk; then the capital regulation is unable to prevent moral hazard. Additionally, no single model can guarantee that there will be no suffering from unusual financial market stress situations (Gumerlock, 1996). If a penalty applies, the figure will be significant. Kupiec and O'Brien (1995a) suggest comparing the internal model with a benchmark measure of risk exposure as an alternative to verifying an internal model. However, there is no regulatory benchmark model available as a basis for comparison. To select a benchmark, we would need to examine all the models used by banks. This study thus concludes that the pre-commitment approach is irrelevant for Indonesia, especially given the poor state of development of internal risk management-processes.

To decide which models are best depends on what criteria are employed. From the accuracy point of view, the GARCH approach is much better than both the BIS standardised method and EWMA. However, this model needs frequent adjustment to fit with new data, more complicated and is time consuming due to the need to add new data to ensure that the pattern of the process (mean and variance processes) remains fixed (Jacquier, Polson, and Rossi, 1994). As soon as we suspect a pattern change, we need to rerun the models by incorporating new data to identify the new mean and variance processes.

[3] The pre-commitment approach allows a bank to set in advance its own capital requirement, with penalties imposed if it suffers cumulative losses larger than its committed capital at any point during the reporting period.

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