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CAPITAL ADEQUACY ASSESSMENT IN INDONESIA:
An Empirical Study

by
Wimboh Santoso

A Doctoral Thesis
Submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy of Loughborough University

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Abstract

Many Indonesian banks suffered problems and some even failed in the early 1990s. This provided evidence that risk-based capital adequacy regulation in Indonesia had failed to prevent banks from taking excessive risks. Such observations provide the motivation for this thesis 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 thesis includes an empirical study to identify the determinants of problem banks in Indonesia using a logit fixed-effect model. The model also can be used as an “early warning” device in banking supervision. 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 excessive foreign exchange rate risk.

This thesis also finds that the adoption of risk-based capital adequacy regulation in Indonesia contains some deficiencies, such as focusing only on credit risk (ignoring market risk). This study suggests that market risk should be included in capital adequacy assessment and a number of alternative models of risk assessment [exponential weighted moving average (EWMA) and generalised autoregressive heteroscedasticity (GARCH)] are analysed.

The results of the empirical study show that the inclusion of foreign exchange rate risk in capital adequacy assessment results in a higher capital requirement than that resulting from the application of the BIS's standardised methodology. This study also finds that the decay factor of 0.94 suggested by J.P. Morgan (J.P. Morgan, 1995, 1996) is irrelevant for IDR (Indonesian Rupiah) exchange rate returns. Additionally, assessment of foreign exchange rate risk using GARCH suggests a lower capital charge than that applicable under the BIS’s standardised methodology and EWMA. The policy implications of these findings are also considered.
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<td>Absolute percentage error</td>
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LDR  Loans to deposits ratio
LIBOR  London inter-bank offered rate
LM  Lagrange Multiplier
LPR  Loan provisions to total loans ratio
MA  Moving average
ML  Maximum likelihood
RMSE  Root Maximum square erro
OIR  Operating income to total income ratio
OLS  Ordinary least squares
OTC  Over the counter
PACF  Partial autocorrelation function
PFEB  Private foreign exchange bank
PNFEB  Private non-foreign exchange bank
RDB  Regional development bank
RLLF  Restricted log likelihood function
ROA  Return on assets
ROE  Return on equity
ROI  Return on Investments
SBC  Schwarz bayesian criterion
SML  Security market line
TOWRA  Total of weighted risk assets
TUFF  Time until first failure
UK  United Kingdom
US  United States of America
ULLF  Unrestricted log likelihood function
VaR  Value at risk
VU  Volatility of underlying
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Chapter 1

Introduction

1.1. Bank reform in Indonesia

The central bank of Indonesia, Bank Indonesia (BI), has had experience with bank failures since 1967. At that time, there were seven state banks, 11 foreign banks and more than 100 private banks. Many of the private banks had suffered difficulties in the previous three years because of defaults by their borrowers as a result of high inflation and the introduction of a stabilization program by the government (devaluation of the currency). In August 1967, a banking crisis occurred when 20 private banks were suspended and placed under temporary central bank supervision (Wardhana, 1981, pp.339-57).

Between 1967 and 1983, the central bank imposed tight regulation, especially for private banks. The main purpose was to improve the stability of the banking system with by minimising private bank failures. One of the policies adopted by the central bank was encouraging the private banks to merge with others, to enhance their ability to compete with the state banks which were major players in the banking industry. Finally, the authorities succeeded in reducing private bank number from more than 100 in 1967 to around 70 by 1983 (BI, 1994).

The first deregulation of the banking industry occurred in 1983 and was followed by further bank reform in October 1988. Between 1983 and 1988, almost no bank fell into serious financial difficulty, although fraud affected some small banks. However, after 1988, a large number of banks failed for various reasons. The main content of this section covers the wider issue of bank failure after the banking reform.

Since bank reform took place in 1988, the Indonesian banking industry has experienced problems. We can see that every year since then there have been banks in financial
difficulties. The question that needs to be addressed is: what went wrong with the reform? Is it that banks in Indonesia are not capable of coping with free market competition (traditionally, they just concentrated on internal group loans)?

BI itself did not know what to do. Some minor adjustments were implemented for both more relaxed and tighter regulation. Responses from the banks were unpredictable and sometimes were at variance with BI's expectation. That is why, according to some critics, BI - the only authority responsible for bank supervision - was not in a strong position to execute its function as a bank supervisor.

Evidence suggests that some banks were exceeding the legal lending limit without receiving any warning from BI to follow the rules (see the failure of Bapindo in Section 1.6.3) Finally, some banks suffered illiquidity. There may have been some constraints on BI in its efforts to bring the banks into compliance with the rules, because of a lack of qualified personnel, political issues, lack of independence, and inappropriate regulation.

Finally, the most significant disturbance in the Indonesian banking sector occurred after July 1997 when the USD/IDR exchange rate dropped gradually from IDR 2,500 to IDR 10,000 in March and to 15,000 in June 1998 (the IDR/USD exchange rate sometimes depreciated above IDR 15,000 at the beginning of 1998). Depositors converted their money from IDR to foreign currencies because they lacked confidence in the IDR and the banking system in Indonesia. As a result, many banks were unable to carry on their operations without fresh funds from the government. However, the government only bailed out "sound" banks; 16 banks were closed in November 1997; 7 banks were suspended from operation in March 1998; and around 40 banks were classified as being "in emergency" in April 1998 and put under the control of the Indonesian Bank Restructuring Agency (IBRA). Finally, 38 banks were closed in March 1999. The economic turmoil since the middle of 1997 provides strong evidence that banking supervision and regulation in Indonesia needs to be restructured. The above cases also support the suggestion that there must be something wrong with banking regulation in Indonesia.
1.2. Problems in bank regulation in Indonesia

Under the existing regulations, the authorities have experienced difficulties in detecting problem banks at an early stage. My view is that banking regulation in Indonesia still contains a number of deficiencies.

First, risk-based capital requirements which rely solely on credit risk fail to assess the true risk in banks. Theoretically, bank risks comprise not only credit risk, but also interest rate risk, foreign exchange risk and other risks. This situation encourages banks to ignore risks which are not covered in the CAR. There are many internal reasons for banks doing so, such as lack of knowledge of risk management and it is being too expensive to add more capital. This study finds that current capital requirements ignore interest rate risk and foreign exchange rate risk, with the result that banks would probably break the trigger of the minimum capital requirement if these were included in the assessment.

Second, under the BIS risk-based capital regulation, all loans to non-banks have the same risk weight. Good-quality loans attract the same risk weight as bad in the assessment. In an extreme case, a bank may not get any revenue from doubtful loans, yet the authorities require the same capital for both good and doubtful loans. This example also shows that the expected cash flows for the doubtful loans may be zero, unless the bank sells any collateral taken, but the current minimum capital adequacy regulation does not cover this issue. In addition, bank managers still find loopholes to escape the regulation. For example, bank managers may accrue interest revenues in their accounting system. Although, under this treatment, the payment of interest looks plausible on the borrowers' account balances, there is, in fact, no fresh money coming into the bank. This situation is not accounted for by the minimum capital adequacy regulation. Finally, some banks apparently have negative economic values of capital without the awareness of the regulatory authorities.

\footnote{The Indonesian government has adopted the BIS minimum capital adequacy requirements since October 1988.}
Third, under the BIS risk-based capital regulation, capital is measured on a book value basis. Actually, the economic values of capital change continuously in line with changes in the values of assets and liabilities. The economic values of assets and liabilities change as a result of changes in asset quality, volatility in interest and foreign exchange rates, and the change in values of intangible assets. The real value of capital can be expressed by market share prices.

Fourth, the risk assessment methodology used fails to capture the actual performance of the management. There are two issues here. First, the methodology lacks the ability to capture management behaviour. Second, there are insufficient guidelines for bank supervisors to assess management performance. In too many cases, immediately before being declared a “problem” bank, the management had been given a good score in management appraisal. Later on, the authorities became aware that the information delivered to them was biased. This shows that bank supervisors failed to carry out their tasks properly.

Fifth, earnings ratio assessment is just based on the accounting record and the link between the ratio and capital is not considered. The accounting ratio method is incapable of assessing the capability of banks to produce earnings in the near future. As we have already discussed, some banks can accumulate unrealised interest revenues in their accounting system. In this case, earnings ratios fail to capture the true performance of banks.

While other criticisms may be levelled against the BIS proposal (BIS, 1988) we have enough evidence to say that current capital adequacy regulation is imperfect. Therefore, banking regulation in Indonesia needs to be re-evaluated and adjusted in the direction of further enhancing prudence.
1.3. Basic concept of risk in finance

In general, risk is defined as the probability of success or failure, where success is making a profit and failure is losing money on an investment. In finance, risk is associated with the degree of fluctuation in generating return whether measured by return on investment (ROI) or by the rate of return on securities.

According to Lee and Finnerty (1990, p.157) and MacNew (1996), risks can be classified based on their sources, namely: business risk and financial risk.

First, business risk (or operating risk) is the risk which refers to the degree of fluctuation of net income and cash flow associated with different types of business and operating strategies. It is assumed that ROI is a variable measurement for making profit and its variance reflects its fluctuation. By transforming to an equation we get a formula to measure expected ROI associated with a particular risk:

\[
\text{expected ROI} = \bar{x} = \sum_{i=1}^{n} X_i P_i, \quad \text{and}
\]

\[
\text{variance of ROI} = \sigma^2 = \sum_{i=1}^{n} (x_i - \bar{x})^2 P_i
\]

where \( P_i \) = probability of occurrence of the \( i^{th} \) level of the economy and \( X_i = \text{ROI at the} \ i^{th} \text{level of the economy} \) and \( n = \text{the various sources of incomes} \ (i = 1, 2, 3 \ldots n) \).

This type of risk is more applicable in investment analysis to a non-financial firm, but less relevant for the analysis of overall risks at banks.

Second, financial risk refers to magnification of profit or loss because of the use of debt financing. Therefore, financial risk is related to financial leverage. The financial risk emerges when a bank cannot pay claims to lenders as a result of a shortage in cash inflow. In the early stages this condition is called illiquidity. One of the common measurements of financial risk is a debt-equity ratio. The larger the debt of a bank, the larger the probability
of encountering a financial problem is, because of fixed cash payment to lenders. The measure of a bank's ability to fulfill its long-term claims is called solvency.

If we relate this to bank risk in practice, financial risk may cover earnings risk, liquidity risk, solvency risk, and efficiency risk depending on the purpose of the analysis. We identify earnings risk when the focus of analysis is on the shrinking of revenues because of high interest payments on debts compared to total assets or equities. Efficiency risk is important when the financial analyst is interested in making a comparison between revenues and expenses. Liquidity risk analysis is intended to show the ability of a bank to cover its short-term claims, and solvency risk analysis focuses on the ability of a bank to cover the claims when the bank is liquidated.

It is clear that the degree of financial risk mainly depends on the ability of a bank to cover claims from depositors, lenders and other counterparties. We can apply this risk theory in the banking industry. Generally, a bank's cash flows are from its investments, credits, profits in trading activities, new deposit funds, borrowed funds and various fees and expenses, including interest payments and operating expenses. These cash flows are not always easy for a bank's management to control.

The difference between business risk and financial risk depends on the sources of the risk. Business risk refers to the ability of a bank to generate revenue from investments or credits. Financial risk refers to unexpected events which affect the values of payments and revenues associated with commitments in the banking or trading books. The relationship between financial risk and business risk is shown in figure 1.1.
The figure shows the relationship between business risk and financial risk. The sum of business risk and financial risk is called the total risk. There is no relationship between the business risk and leverage. The business risk is constant whatever the size of leverage shown by line AB. The financial risk increases along the line OD.

Sharpe (1964) and Litner (1966) developed an asset pricing model which not only determines the value of an efficient portfolio, but also the value of an individual security. They focus on the pricing implications of that area of risk which can be eliminated through diversification as well as that which cannot. In their analysis, they distinguish between systematic risk, or market risk, and unsystematic risk. Systematic risk is one of the components of risk in portfolio investment and results from the tendency of stock prices to move together with the general market. The prices of some stocks and portfolios are
sensitive to the prices of other stocks in the market, while others show more independence and stability. A measure of the sensitivity of a portfolio to the market, based on its past record, has been designated by the Greek letter beta ($\beta$). Unsystematic risk is the fluctuation which may occur as a result of variation in an industry or a firm because of internal factors, such as a labour strike or a resource shortage. A bank with excessive trading activities normally uses this theory to analyse its portfolio investment.

Sharpe (1964) also suggests that we can derive a capital asset pricing model (CAPM) by employing beta risk in the model given certain assumptions, such as that there is an efficient and perfect market, investors being risk-averse, and that there are no transaction costs\(^2\). Sharpe concludes that there is a linear relationship between returns and risks except in the region of extra high risk.

CAPM is defined by the following equation:

$$E(R_i) = R_f + \beta_i [E(R_m) - R_f]$$

(1.3)

where, $E(R_i)$ = the expected rate of return for asset $i$; $R_f$ = the risk-free rate; $\beta_i$ = the measure of systematic risk (beta) for asset $i$; and $E(R_m)$ = the expected return on the market portfolio. The trade-off between risk and return is called the Security Market Line (SML) as shown in figure 1.2.

\(^2\) See F. Cheng Lee and Joseph E. Finnerty, Corporate finance: Theory, Method, and Application, 1990, p.191
1.4. Bank risk classification

In practice, there are many risks at banks. Different researchers apply different risk headings depending on the purpose of the studies. Wall and Eisenbeis (1984) and Rose (1989) employed profitability and cash flow variables to examine bank risks. Other authors, such as Saunders and Yourougou (1990), adopt Stone's model (1974) which employed two factors: a market and an interest rate model in order to compare the market and interest rate risks of portfolios in banking firms and commercial firms.

To assess bank risks, Isimbabi (1994) and Dietrich and Weinstein (1989) compared the sensitivities of the stock returns of banks, other financial firms and non-financial groups to inflation, industrial production, the term structure, and default risk by adapting the multi-
factor model of Chen, Roll and Ross (CRR), (1986). Their results indicate that default risk is significant in addition to the term structure variable for banks and some of the other groups. Isimbabi (1994) conducted an empirical study with regard to a comparative analysis of the market perception of the risk of the banking sector and non-financial (commercial) sectors. The study not only focused on market and interest rate risk but also covered default risk. All these studies assess the risk of banks from different points of view.

From the various studies mentioned above, we can conclude that there are many types of risks at banks. Market risk, interest rate risk and default risk are the components of a bank's risk which may be measured by profitability and cash flow. If we relate to risk theory, which has already been mentioned in the previous section, security prices, foreign exchange rates and interest rate risk reflect systematic risk. This conclusion is based on the argument that market price volatilities and interest rate volatilities will affect any firm which is involved in investment in securities markets as well as debt financing. The market risk for each firm may differ from others as a result of the different exposure of their portfolios. The sources of default risk normally emerge from a specific condition of borrowers or counterparties, and this only affects the lenders. Therefore, we cannot regard default risk as a systematic risk.

Some economists have pointed out that there are some risks which arise from banks' activities such as market risk, economic environment changes (Flannery and Guttentag, 1979, Guttentag and Herring, 1988) and management and operations risks (Mullin, 1977; Graham and Horner, 1988). Other kinds of risks may cause significant damage before their dimensions are well understood, including interest rate risk and sovereign risk (Stanton, 1994). The following outline shows various bank risks in practice.

According to Gardener, a bank's risk consists of general risk, international risk and solvency risk (Gardener, 1986). General risk is a fundamental risk faced by all banks
namely, liquidity risk, interest rate risk, and credit risk. Liquidity risk is the risk of having to cover claims from liabilities on their maturity dates.

Vojta (1973) has yet another view of bank risk. Based on his observation, risk could be defined according to banks’ operations or activities: (1) credit risk (losses on loan portfolios); (2) investment risk (losses in the value of marketable securities and fixed assets); (3) liquidity risk; (4) operating risk (losses arising from operating errors and inefficiency; (5) fraud risks; and (6) fiduciary risk (losses arising from improper discharge of fiduciary responsibility).

Revell (1975) argues that Vojta focuses on only some of the possible sources of risk, so that the adoption of his risk classification could be very dangerous for regulators or depositors. Revell mentions that Vojta’s list does not identify foreign exchange rate risk as an important source of bank losses, nor interest rate risk as a source of risk, apart from their effect on asset prices. Inflation could also be considered an important cause of losses. Finally, according to Revell, the most important risk is the loss of confidence by depositors. Compared to Vojta, Revell describes risks more comprehensively and includes the source of each risk. He omits fraud and fiduciary risks because these risks can be insured against in most countries due to the development of insurance markets. Moreover, Revell gives a more detailed description of certain risks.

Maisel classifies the risk of banks to be interest rate risk, operating risk and fraud (Maisel, 1981, pp.1-40). Interest rate risk contributes significantly to insolvency. When interest rates rise, banks must pay more for interest costs on liabilities. The degree of danger depends on the schedule of cash flows from assets and liabilities and on the probable magnitude of shifts in the interest rate structure.

Risk in a modern bank comprises more types of risk than in traditional banks. McNew (1997) suggests a more comprehensive risk classification in the case of modern banks. According to him, financial risk in a modern bank comprises credit risk, market risk,
liquidity risk, operational risk, regulatory risk and human factor risk. The detail of each risk is shown in the following figure:

**Figure 1.3**

Components of Financial Risk

From the discussion above, we can derive a number of conclusions.

First, the risk components defined by the authors above are fairly closely related to each other, but since they classify the risks under different headings they can seem to overlap with each other.

Second, solvency risk covers the major components of risk. It means we could hypothesize that solvency plays the most significant role in bank failure and that other risks, such as credit risk, market risk (including exchange rate risk), interest rate risk and operating risk, are components of solvency risk. Solvency risk can be defined as the risk
which is associated with the market value of equity in order to satisfy stakeholders that the bank is still solvent. If the value of equity is low, the regulator will require the bank to add more capital or to reduce risk by restructuring its risky assets to the level which increases the economic value of the equity.

Third, there are also some risks which are not related directly to solvency risk. Banks may find difficulties in controlling these risks because the sources of the risks are mostly beyond the management boundary. The risks are normally associated with prudential operations with which the regulator needs to be concerned before a bank becomes insolvent, such as political risk and fraud.

1.5. Measuring bank risk

The determinants of bank risk can be defined as the factors responsible for variation in the value of the bank itself. Depositors, creditors, insurers and owners will refer to the value of the bank when they assess its risk. The general opinion is that the value of a firm at any time is equal to the present value of expected net cash flows from assets, liabilities and other activities. The risk of banks arises because the expected values of assets change, and alterations in cash flows may either require raising funds at a higher cost than returns on the existing portfolio, or the value of liquidated assets falling below their book values. Bank management, normally, reduces the risk by managing assets and liabilities in such a way that the expected returns of the bank will be unaffected by various changes in the economy, interest rates, exchange rates and customers' behaviour.

Maisel (1981, pp.1-40) describes insolvency as a function of the current economic value of the bank's capital - that is, the present value of the expected cash flows from the firm's portfolio - and the probability that either the expected cash flows or the discount rates at which the flows are valued will alter. Maisel's description implies that the present value of the cash flows, credit risk, interest rate risk, market and exchange rate risk are all brought into consideration. The bank will become insolvent if its accumulation of negative income
is more than its initial capital plus any reserve. Moreover, Maisel mentions that the insolvency of banks, expressed by capital adequacy, may be arise either when the supply of liquidity is very low, when banks cannot pay claims to depositors and debts, or when the market value of the assets reduced by the cost of bankruptcy is less than the value of the liabilities to customers, computed under the assumption that all such claims will be met fully.

From the discussion above, it can be concluded that solvency risk has covered liquidity risk, interest rate risk, and exchange rate risk. Moreover, solvency risk contributes significantly to the probability of bank failure. The risk of the banks becoming insolvent depends on the level of the expected incomes and payments and the variation of the net profit/loss and the initial capital. Therefore, risk measurement should consider the balance sheet income and economic income.

The value of a bank should change over time because the income and future expected cash flows have changed, mainly as a result of the movement of interest rates, exchange rates, market value of assets or liabilities and other activities. Bank records and balance sheets often fail to show such actual changes in the value of assets and liabilities.

There are some components of bank risk suggested by authors which may be very difficult to define. We will focus on solvency risk which is derived from various components of bank risk. Based on the theory of finance, the solvency of a bank will be determined by the value of a bank at any point in time which equals the present value of expected cash flows from its activities. If the instrument is traded in a liquid market, the expected cash flow is just the same as the market value of the instrument (mark-to-market).

An accounting book value which relies on historical values is not real economic value. Therefore, this method cannot be used in capital adequacy assessment for banks. Proper assessment of the economic value of capital requires complicated quantitative calculations
because the value of assets-liabilities changes over a period of time as a result of wealth effects and income affects.

Whatever risk headings are suggested by the authors above, the impact on banks' value will be reflected in solvency which is measured by net present values of cash flows. Finally, we may conclude that solvency is an appropriate measure to represent all risks which are derived from the present value of expected cash flows. This research also suggests that credit risk, market risk (i.e. interest rate risk, foreign exchange rate risk, and price risk) and operational risk are the main factors determining discrepancies between estimated and actual cash flows. Figure 1.4 shows the schema of these conclusions.
Figure 1.4
Concluding Schema of Bank Risk

Assets-liabilities

Unmatched forex positions and exchange rate volatility

Forex risk

Unmatched investments and sources of funds and interest rates

Sources

Undiversified credits

Default risk

Risk factors

Unexpected costs and expenses

Operational risk

Risks

Unmatched investments and sources of funds and interest rates

Interest rate risk

Results

Expected cash flows

Net worth

Cash flows

Liquidity and Solvency
1.6. Cases of bank failure in various countries

1.6.1. Selected bank failures in the US

The first US bank failure was Farmers Exchange Bank, Gloucester, Rhode Island (Sinkey, 1979, p.3). The Providence Gazette reported on 25 March 1809 that the directors and managers of the bank:

"... practised a system of fraud beyond which the ingenuity and dishonesty of man cannot go".

The causes of the failures which happened during the period 1865-1933 vary. The following paragraph will discuss some of the causes of individual bank failures in the US. On 14 April 1865 the First National Bank of Attica (New York) failed. The bank, which as a small one with total assets of $208,106 and capital of $50,000, was the first nationally chartered bank to close. According to Kane (1923, p.36) the failure was caused by

"... injudicious banking and insolvency of large debtors".

The next bank failures were the Venango National Bank of Franklin, Pennsylvania, and the Merchants National Bank of Washington, D.C. (Kane, op. cit. 1923 p.37-45). Venango, with capital stock of $300,000, was closed on 1 May 1866, while Merchants, with capital of $200,000, failed on 8 May 1866. The report of the House Banking Committee indicated that each bank had a heavy business loan concentration on one particular borrower, although not the same one. Consequently, when these two business enterprises failed and defaulted on their loans, which were unsecured, the banks also failed. The managers of the Merchants Bank were characterized as being

"... in the highest degree illegal, improvident, reckless and dishonest"
(Kane, op. cit. 1923, p.38).
The Venango bank was said to have operated in the same manner as the Merchants Bank. Some research has been conducted with regard to the cause of bank failure. A Federal Report (National Industrial Conference Board - 1932, pp.44-5) listed a number of causes as being important in banks closing from 1921-7. Among the internal causes that reflect incompetent or dishonest management the following were listed: (1) a large volume of doubtful, slow, or past-due loans; (2) large loans to officers or directors; (3) defalcation or embezzlement; (4) excessive loans to businesses with which officers or directors were affiliated; and (5) in general, overall poor management. External causes cited were: (1) heavy deposit withdrawals; (2) unexpectedly large depreciation of security investments; (3) the failure of a banking correspondent; and (4) the failure of a large debtor.

Another author (Bremer, 1935, p.99) reported that the failure of national banks in 1925 was because of the following problems: (1) inexperience and mismanagement (50%); (2) unfavourable local conditions (40%); and (3) defalcation (10%).

The most traumatic experience was the "bank holiday" of 1933, when all banks were forced by government to close their operations until they could prove that they had enough capital resources. The banking crisis began in November 1930, initiated by 256 banks failing. In December in the same year, 352 more banks failed. Measured by deposits, the largest bank failure was that of The Bank of the United States. The bank was a Federal Reserve Member, and therefore the Federal Reserve of New York organized a "lifeboat" rescue with the support of clearing house banks. Other countries suffered bank failure as well because the depression in the US had wide-reaching global effects.

Another relapse was followed temporarily by recovery but in January 1932 failure spread to other areas in the US. By 3 March 1933, half of the states were required to declare a bank holiday and banks were closed until 13-15 March, depending on their location (Sinkey, 1979, p.14). On 15 March 1933, about 14 banks were back in business, but about 4,500 banks were not permitted to reopen because they were insolvent or in a condition
requiring restrictions on deposit withdrawals. The number of bank failures for the 1930-3 period amounted to 6,704 banks (Upham and Lamke, 1934, p.5).

When the immediate crisis abated, Congress turned its attention to more permanent banking legislation. The result was the Banking Act of 1933. The purpose of the Act was to provide for safer and more effective use of the assets of banks, to encourage banks to adopt prudent internal controls, to prevent undue diversion of funds into speculative operations, and for other purposes. Among other things, the Act of 1933 provided for the establishment of a Federal Deposit Insurance Corporation, separation between commercial and investment banking, restriction on the use of bank credit for speculative purposes, more stringent charting requirements for national banks, prohibition of interest payment on demand deposits, removal of bank directors, and branching by nationwide chartered banks to be subject to the same state law imposed upon state-chartered institutions.

From 1 January 1934 until 5 September 1978, 689 banks failed. Four hundred and ninety (490) banks (71.1 %) were closed over the nine-year period 1934-42 or approximately 54 banks per year. From 1943 up to 1977, only 193 (28.9%) banks failed, or about 5.5 per year.

As of 31 December 1974, there were 251 uninsured banks or non-deposit trust companies in the US. These uninsured institutions accounted for only 1.7 percent of the population of 14,481 commercial banks and for only 0,95 percent of $754 billion in total deposits at commercial banks. From 1943 until 1974, only 121 insured banks failed, on average less than four banks per year. On the other hand, 37 non insured banks closed during the same period. In contrast, in 1975, thirteen insured banks failed and in 1976 sixteen banks closed.

A Federal Deposit Insurance Corporation (FDIC) study conducted by Hill (1975, pp.1-2) based upon 67 insured banks that failed between 1960 and 1974, indicated that there were three major causes for the banks’ failure. First, 38 of the failures were due to improper loans to officers, directors, or owners and in 20 of these 38 cases misuse of brokered funds
was involved. Second, defalcation, embezzlement, or manipulation were important in 21 of the failures. And third, eight of the failures were blamed on managerial weaknesses in loan portfolio supervision.

In 1979, First Pennsylvania, then the twenty-third largest bank in the US, reported a loss in net earnings, after a provision for loan losses and taxes, of $5 million. The bank was founded in 1782 and recognized as the first private bank established in the US. In 1967, the bank's equity was equal to 8.7 percent of net earning assets. In 1979, the ratio dropped to 4.2 percent. The share of earning assets financed by interest-bearing short-term funding liabilities was 26 percent in 1967 and rose steadily to 74 percent in 1979. Earning assets increased by 400 percent while demand and saving deposits rose only 40 percent. Risks were augmented by active trading in securities and mortgages. As interest rates rose during the decade, net operating earnings before loan losses of the bank declined. At the same time, earnings become more variable (Maisel, 1981, pp.8-10). The condition implies that the greatest danger to financial institutions arises from interest rate risk when the funding management relies on short-term sources and long-term lending. Interest rate risk depends on the net difference in the maturities of a bank's assets and liabilities. If the average maturity of the liabilities is shorter than the average maturity of assets, the value of capital will deteriorate when interest rates rise.

Spero (1980) outlines further detail concerning the failure of Franklin National Bank (FNB). The bank, which was considered as the 20th largest bank in the US, suffered a crisis in May 1974. The authorities had known that the bank had a problem from the beginning as shown when the Federal Reserve Bank refused the proposal of FNB to take over another institution at the beginning of May with the reason that the bank had expanded too quickly. Two days later the bank announced that it had suffered very large foreign exchange losses and had no money to pay quarterly dividends. Moreover, the bank also made a large volume of low-quality loans as a result of growing too rapidly. The depositors withdrew their funds and the money market was reluctant to lend money to the bank. The Federal Reserve Bank lent Franklin up to $1.75 billion. Because it was insured
by the FDIC, small depositors who had less than US$100,000 on deposit did not withdraw their money. As we know, the FDIC Act 1933 mentions that:

"The maximum amount of the insured deposit of any depositor shall be $100,000" (Symons, 1991, p.81).

Finally, in October 1974, the bank was taken over by a consortium of seven European banks and European-American banks. Actually, the sources of the problem were not only foreign exchange losses, but also domestic problems such as rapid growth and poor management.

From the experience of the Franklin bank, we can conclude that loan losses were the initial problem of the bank as a result of weak loans and funding management. The speculation in foreign exchange trading was expected to generate profits to settle the loan losses. But the market moved in an adverse direction and the heavy losses from foreign exchange trading pushed the bank into deeper problems. Weak internal control also allowed speculation to occur because the Franklin traders could engage in high risk transactions without any monitoring by their internal auditors/managers.

US bank failures still continued up to late 1990, as reported by Sarah B. Kendall (1994). Between 1934 and 1981, the FDIC had made a profit, but later on, by closing approximately 15 banks per year, it incurred a deficit for the first time in 1991. Moreover, the FDIC estimated that 200 banks would have been closed in 1992 without their intervention, which increased the insurance fund deficit to $14 billion (Kendall, 1994, p.542). Savings and Loan institutions also had very high failure rates. According to Barth, from 1980 to 1990, 1,730 saving and loans institutions suffered failure (Barth, 1994). Finally, in 1984, the eighth largest bank in the United States, Continental Illinois, declared the need for an additional injection of funds from the Federal Reserve of up to $6 billion in order to cover claims from creditors. The source of the bank's problem was high
leverage combined with a risky portfolio in its reckless pursuit of market share (Kapstain, 1994).

1.6.2. Selected bank crises in the UK

The failure of banks has occurred since the 15th century when the Medici bank failed after the English sovereign defaulted on his debts. In the UK, Gurney and Company Ltd failed in 1866 (Batchelor, 1983, pp.4-12). At first, Gurney was a prosperous financial firm involved in banking and bill brokerage. In 1856 and 1857 the bank changed its management. Unfortunately, the new management adopted an unsound strategy by taking bills of dubious quality and allocating loans with poor collateral. In 1865, the firm reported losses of £3-4 million. Moreover, in 1866, some speculative firms and associated contracting firms linked to Gurney through finance bills, also failed. Some depositors suspected that Gurney was suffering financial problems and they withdrew their money. On 10 May 1866, the bank was short of liquidity and the Bank of England refused to inject fresh funding. Gurney was reported as bankrupt on the same day. The source of the problem in the Gurney case was the poor quality of finance bills.

Baring Brothers & Co, the large international merchant bank, nearly failed in 1890 (Batchelor, op. cit. pp.12-18). The bank was founded in 1763 by John and Francis Baring to finance their customers in textile trading in Europe and Latin America, but in 1821-2, the loan portfolio was expanded to include Mexico and Latin America. Baring, together with other London-based merchant banks, specialized in long-term sterling lending to foreign governments and public bodies. Most of their loans were concentrated in Europe and Latin America. In the late 1890s, the loans concentrated in Argentina and Uruguay accounted for over 75 percent of the bank's total portfolio for government projects. European loans were less than 10 percent by 1890. The Argentinian government found difficulty in paying interest and negotiations to find new investors were unsuccessful. However, the bank and the UK government feared a massive drain of foreign capital from the UK if they let the bank go bankrupt without any solution, and persuaded other banks
to inject funds into the bank. Finally, Baring's liquidity problem was solved by obtaining £17 million from other banks and discount houses and the impact on the financial market was small. From the Baring experience, we can deduce that the source of the problem was counterparty risk. Normally, banks would reduce the risk by diversifying loans geographically and across more business activities.

Johnson Matthey Bankers (JMB), one of the Johnson Matthey Group members, had been rescued in October 1984 when it was believed that the loan problems would spread to the whole group. As we know, Johnson Matthey is a prominent dealer in gold bullion and precious metals and it was feared its failure would damage London's reputation in commodities trading. JMB got into trouble because it managed to acquire loan losses of £245 million on a loan portfolio of only £450 million, so it had to write off more than its equity base which was less than £120 million (Hall, 1987).

The Bank of Credit and Commerce International (BCCI) case exploded in 1991 because of a variety of criminal activities, such as money laundering for drug dealers. BCCI was declared insolvent in the summer of 1991, and the Bank of England closed it in July 1991. Because of this case, UK banking supervisors encountered some criticism for not closing the bank at an earlier stage, (Hall, 1992). The BCCI, founded by Agha Hasan Abedi on 21 September 1972 in Luxembourg, had been recognized as indulging in fraud and illegal dealing since 1975 when the US authorities refuse to allow the bank to take over two New York banks for the main reason that the owner, Abedi, was failing to disclose details about his company.

A subsidiary was opened in Panama on 22 April 1980. When General Manuel Noriega came to power in 1981, Marcela Tason, Noriega's secretary, was one of its early customers in Panama. Other names who have been recognized as smuggling drugs had opened accounts in this bank such as Pablo Escobar (Kochan, 1991, pp.93-4). In the BCCI scandal, we can raise questions about the role of both the home-country as well as the host-country authorities in supervising the bank. BCCI was based in Luxembourg, but the
home country authorities lacked the resources to control its operation. Host-country authorities attempted to monitor the foreign bank's branches, but they were unable to access all the information on the bank. Criticism of the Bank of England also came from the House of Commons Treasury and Civil Service Committee (in this discussion, we will use the term "Committee"). In the Committee's report for the parliamentary session 1991-1992, the Committee criticised the Bank of England for not closing BCCI down earlier, forcing the banking group to change its structure to facilitate consolidated supervision by a single lead supervisor, or sponsoring "single auditor" audits, and for pressing Price Waterhouse, the sole auditor to BCCI after 1987, not to qualify BCCI's 1980 accounts.

The Baring Group plc, a British merchant bank, suffered massive losses from unauthorized derivative transactions conducted in its subsidiary, Baring Futures Singapore (BFS), at the beginning of 1995. The bank was subsequently taken over by the Dutch Bank ING. The UK Board of Bank Supervision subsequently produced a report highlighting the lessons to be learnt from the collapse. Nick Leeson, a Singapore-based office trader, built massive positions in futures contracts by betting that Japanese stock prices would rise, with minimal supervision from headquarters. As the market fell, Leeson apparently kept doubling and re-doubling his positions. Losses were estimated at more than US$1.2 billion or about triple the bank's capital (Clifford, 1995).

1.6.3. Individual bank failure cases in Indonesia

As we have already mentioned, the rapid growth in the number of banks, offices, and their exposures, a shortage of professional managers and deficiencies in bank supervision are potential sources of banking crises. In fact, several banks have suffered financial problems, for example Bank Umum Majapahit, Bank Pertiwi, Maranu Bank, Bank Bukopin, Bank Sampurna, Bank Duta, Bank Summa and Bapindo. The central bank officially announced that these banks had financial problems although the public did not know the exact number of banks which suffered similar financial problems because of asymmetry of information in
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the banking industry. Bapindo's failure was the latest in a series of crises in 1994 that have heightened fears of a financial breakdown.

Bank Umum Majapahit suffered problems in 1987 because the owners engaged in insider transactions using illegal CDs. The dishonesty was exposed when they failed to meet their liabilities. Certain unauthorized borrowers were also involved. Depositors claimed their refunds, and the case was eventually reported to the central bank. In this situation, the bank is officially responsible for all liabilities whether the deposit certificate is original or counterfeit. All insider transactions were undertaken by dishonest managers because all transactions were labelled with the name of the bank. Bank Indonesia restricted the bank to participating in clearing activities, and some depositors took the bank managers to court. Finally, a consortium of other banks took over the bank with the aim of maintaining public confidence in the banking system in Indonesia. However, its re-opening was put on hold until the government revoked its licence in November 1997.

The Pertiwi case exploded in 1986 because of two major reasons that were interrelated, namely, loan concentration and mismatch of funding. The case began with loan concentration. The majority of its loans were concentrated on properties when there was a price boom in the late 1970s when, as we know, the Indonesian economy was booming because of high oil prices in the 1970s. When the oil price dropped in the early 1980s, demand for housing automatically went down because the government maintained tight liquidity in order to ensure that the government kept enough foreign reserves to back up its balance of payments. As the mortgage demand dropped in a period of tight liquidity, the revenues of housing construction firms fell far below estimates and repayments to the banks were delayed. Banks with long funding positions suffered from lack of liquidity as a result of the shorter term of deposits. Banks with strong group companies did not encounter any problems because other group members provided funds instantly. But, for the weak group companies, the group members did not have the capability to support the banks. Finally, the management of the bank declared the bank illiquid when the rush occurred. Bank Indonesia closed the bank's operation until the bank settled the claims from
the clearing system. Finally, other banks took over all assets and liabilities under guidelines from the central bank with the aim of preventing instability in the banking system.

The Pertiwi's case caused the Maranu Bank to suffer a lack of liquidity as a result of a large amount of inter-bank loans to Pertiwi. When Pertiwi suffered a lack of liquidity, Maranu had the same problem; moreover, the deposit customers knew about the case and panic could not be avoided. As a general rule, the banks which failed to cover the claims from the clearing system were restricted to continuing their participation in the clearing system. Therefore, Bank Indonesia removed Maranu from the clearing system before the bank was taken over by other banks.

The three bank failures that we have discussed above occurred before the banking reform of 1988. Even after the reform, the Indonesian authority had experience of bank failure. Even banks which were amongst the 10 largest banks in Indonesia failed.

The first large bank to fail was BUKOPIN. This bank suffered from significant doubtful credits without any secure collateral. The case was not exposed openly by the authority to the media because the bank is a cooperative bank, working on behalf of the government to elevate the performance of small scale business cooperative firms in Indonesia. The bank was rescued by Bank Indonesia to prevent it from collapse.

The second large bank to fail was Bank Duta, a private bank, which had 73.39 percent of its shares held by three charities chaired by President Suharto (Schwarz, 20 September 1990). At first, nobody believed that Bank Duta had suffered a crisis. Financial reports showed a conservative performance with credits accounting for Rp. 1,700 billion (approximately US$0.85 billion) of Rp. 2,300 billion (approximately US$1.15 billion) of total assets, but the capital base was only US$164 million (Vatikiotis, 13 September 1990). Further, to Bank Duta, it appeared that reserves for loan-losses were below those of other private banks. Nobody suspected, not even the authority, that the idle funds were invested in trading activities. Regulation restricts national private banks to running a net
foreign exchange position of not more than 25 percent of capital. Indonesian bankers said that Bank Duta must have run an open foreign exchange position of around US$1-2 billion-equals to between 610% and 1220% of the capital base- before the collapse and the bank also speculated in the US$/IDR exchange rate both its own account and on behalf of individual clients. That trading was not recorded properly and thus not reflected in the financial reports. The bank thus maintained large exposures in foreign currency positions; therefore, when exchange rates moved in an adverse direction, the bank was illiquid and unable to settle claims from creditors. Finally, the bank announced on 4 October 1992 that losses resulting from foreign exchange trading had reached US$ 419.6 million (Schwarz, 18 October 1990). Ronald Stride, a Booz Allen & Hamilton Vice President who advised several Indonesian banks, said:

"Indonesian banks, unsophisticated in foreign-exchange markets, have been on the losing side of a zero-sum game and they are getting out" (Tempo, 18 Oct. 1990).

The statement above reveals that banks in Indonesia did not have enough experience in foreign exchange trading compared to other traders in the markets. Finally, charities chaired by the President of Indonesia, Suharto, rescued the bank with fresh-money and replaced the management. Dicky, who was a managing director in charge in trading, was sent to jail on a corruption charge for running dishonest foreign exchange transactions.

The third large bank to fail was Bank Summa in November 1992. The bank was formed in 1988 from an existing bank - Bank Agung Asia - in the same year when deregulation triggered an explosion in the number of new bank licences approved. The slowdown in property demand in 1990 was the main source of the crisis. The bank was faced with a financial crisis because of large loan exposures to shareholders' group companies which were involved mostly in properties. The bulk of this debt was the result of loans to finance Summa Group's involvement in the Indonesian property market from 1989-90, when real-estate prices were at their peak. The Summa Group, which was set up in the late 1970s,
was interested in insurance, leasing, office development, hotels and plantations. Most of Summa's non-performing loans were made to Summa Group, headed by the eldest son of Soeryadjaja (the owner of Bank Summa). According to the Far Eastern Economic Review, more than half of Summa's non-performing loans were made to companies within the Summa Group, (Azman, 1992).

The problem banks also include some medium or small banks such as Bank Sampurna. The bank was established after the banking reform of 1988. The source of problems also came from doubtful credit to shareholders' group companies. Bank Danamon, a top 10 private bank, took over the bank in early November 1992. There may have been some other problem banks in Indonesia, but the information has not been revealed to the media.

The last case exposed to the public before the banking crisis in 1997 was Bapindo, a state bank, in 1993. The case was officially disclosed at the parliamentary hearing by the financial authorities, namely, the Minister of Finance and the Governor of the central bank. One of the parliamentary members had been asking about the performance of a Bapindo borrower, Golden Key, which was suspected of having financial problems. The borrower had outstanding credit of Rp.1,300 billion (US$ 650 million) from Rp.9,600 billion (US$4,300 million) of total credit or 13.5%. The bank's capital was Rp.700 billion (US$350 million). Therefore, the credit of the borrower was 140% of total bank capital. Actually the ROA of the bank had shrunk from 2.1% in 1987 to 1.8% in 1988, 1.1% in 1990, 0.31% in 1990 and 0.26% in 1993.

The banking crisis since 1997 has occurred as a result of the gradual fall in the Indonesian rupiah (IDR) exchange rate since July 1997. The USD/IDR exchange rate dropped from IDR2,450 per US dollar in July 1997 to IDR11,000 per US dollar in March 1998. The IDR depreciated significantly in March 1998 when the IMF released a negative report on the Indonesian budget deficit. The depreciation of the IDR caused people to have less confidence in it and to convert their deposits from IDR to US dollars or to other strong currencies. The more people wanted to buy US dollars, the more US dollars disappeared.
The crisis began in July 1997 when the IDR/USD exchange rate was IDR2,450. The first attack caused the IDR to sink to the level of IDR 2,511. In response to the speculation, Bank Indonesia (BI) increased the spread for US dollars (i.e. the difference between buying and selling rates) from 8% to 12%. The widening of the spread had been used by BI several times to curb speculation in IDR. The spread was only 2% in April 1995, but rose to 3% in February 1996, to 5% in July 1996, and to 8% in September 1996. The widening of the spread in April 1995 was to prevent a rush into dollars because of the death of Mrs. Suharto, while other widened spreads were intended to counter rushes into dollars because of the rumours concerning devaluation of the IDR. However, this strategy was no longer valid in the period after July 1997. The demand for US dollars was very strong and the intervention band of BI (i.e. the market spread at which BI has to intervene) was not effective in slowing down the demand. The exchange rate of the IDR was still unstable, strengthening for a few days by a few points and then depreciating again. To avoid a further wasting of reserve funds, BI cancelled the intervention band and let the IDR float on the market when the exchange rate stood at IDR2,800 to the dollar.

The exchange rate turmoil affected significantly the weak banks which had already suffered financial problems before the crisis. Finally, the government revoked the permit of 16 private national banks on 1 November 1997, closed 7 banks in April 1998 and 38 banks in March 1999. The sources of problems for those banks were mainly illiquidity and insolvency as a result of credit defaults, fraud and liquidity mismatches. With their liquidity mismatched, these banks were sensitive to the rush to dollars. None of those banks’ financial problems occurred because of losses in foreign exchange trading (Gatra, 8 November 1997). Bad loans occurred in internal group companies where the amounts had already breached the lending limits. The exchange rate turmoil affected indirectly the liquidity of banks through the rush to draw money to be placed in other banks or overseas banks.

In another initiative, the government formed the Indonesian Bank Restructuring Agency (IBRA) at the end of January 1998 to restore the solvency of sick banks. In April 1998,
there were 54 banks under the control of this agency which comprised four state banks, 11 regional development banks and 39 national private banks. The criterion of a sick bank is either when emergency funds from the central bank amount to more than 200% of the capital base or the risk-based capital adequacy ratio (CAR) is less than 5%. To restore public confidence in the banking system, the government announced its intention to fully protect depositors' money. Most of the sick banks suffered illiquidity and insolvency as they posted huge credit defaults and suffered large withdrawals. The only bank which suffered significantly from foreign exchange trading losses was Bank Exim, a state bank.

From the banking crisis in Indonesia, we can conclude that the depreciation of the IDR did not directly cause bank failure in Indonesia except in the case of Bank Exim. However, the exchange rate turmoil made depositors less confident in the banking system in Indonesia and encouraged depositors to put their money in foreign currencies in overseas banks. Finally, the small and medium sized banks suffered the most. For large banks, problems normally arose because of defaults by borrowers which made the banks illiquid or insolvent. Bank Exim, a state bank, is the only bank which got into trouble because of losses in foreign exchange trading.

From these experiences, it can be seen that the Indonesian banking industry suffered problems mostly because of default by credit borrowers. Most cases cited above indicate that the sources of the problems were credit default mixed with significantly unmatched funding positions; some of them because of fraud mixed with large credit default (such as Bapindo); and some of them because of foreign exchange losses (such as Bank Duta and Bank Exim). This qualitative evidence of problems at banks will be used to suggest the main variables to be employed in the analysis of problem banks in Indonesia by transforming the sources of problems into financial ratios.
1.6.4. Bank failures in other countries

In July 1982, the Italian authorities seized the country's largest bank, Banco Ambrosiano, SpA because of massive problem loans, worth up to $1.4 billion, to 15 front companies in Panama. These loans were under guarantee by letters of comfort from the Istituto per le Opere di Religione (IOR), the Vatican Bank, in some cases or were at least under guarantee by direct subsidiaries of the IOR. Banco Ambrosiano posted $700 million of borrowed funds from the Euromarkets. Among the bank's assets were more than $1 billion in overdue foreign loans, and the bank was on the verge of a collapse that would have wiped out the savings of thousands of depositors. The Bank of Italy refused to bail out Banco Ambrosiano Holdings Luxembourg, a subsidiary in Luxembourg, because it should have been subject to supervision by the Luxembourg authorities (Dale, 1992, pp.198-201). As we know, it was only in April 1981 that the Regulator in Italy amended the legislation to comply with the philosophy of the Basle Concordat that the parent bank could pass through financial information of overseas subsidiaries to the parent authority. A series of meetings of seven banks that made efforts to rescue the bank revealed a preference for Banco Ambrosiano SpA to be placed in liquidation and a new entity, Nuovo Banco Ambrosiano, was established. 3

Looking beyond Europe, Australia, Scandinavia, New Zealand and Japan, all have experienced banking crises as well as the US. David Hale (1991) in his paper for the G-7 Council in Tokyo, Japan, November 1991, summarises that the major foreign banks in Australia, for example, lost several billion dollars on loans to property developers and corporate asset traders. The non-performing loans ratio increased to 4-5 percent in 1991 compared with 1 percent in the mid-1980s. This can be contrasted with the situation in Britain, where the ratio of non-performing loans in the country's leading clearing banks had risen to almost 2 percent in 1991 from 0.6 percent in 1987 as a result of credit quality problems with real estate and corporate "entrepreneurs".

3 The information on the Banco Ambrosiano case was derived from various editions of The Banker in 1992.
Information about banking crises was summarized by David Hale (1991) in his paper for the G-7 Council in Tokyo, Japan, November 1991. In his summary, he concluded that the major sources of banking crises were credit problems.

1.6.5. Summary of bank failure cases in various countries

From these bank failure cases, we can conclude that the typical sources of failure mainly came from: first, a maturity mismatch of assets-liabilities associated with changes in interest rates; second, large exposures in foreign exchange and securities lending which turned to losses when adverse changes in market prices and exchange rates occurred; third, doubtful loans to large borrowers or default by borrowers; fourth, management dishonesty or fraud, as happened at BCCI. The qualitative analysis of bank failure in Indonesia will be discussed in the following section.

As for Indonesia, it can be seen that the banking industry suffered problems mostly because of default by credit borrowers. Out of the seven cases cited above, five of them indicate that the sources of the problems were credit default mixed with significantly unmatched funding positions; one of them because of fraud mixed with large credit default (Bapindo); and one of them because of fraud mixed with foreign exchange losses (Bank Duta). This qualitative evidence of problems at banks will be used to suggest the main variables to be employed in the analysis of problem banks in Indonesia by transforming the sources of problems into financial ratios.

From our discussion above, we will now try to draw general conclusions about the causes of unsound banks before we begin to analyse, in greater detail, the determinants of potential problems at commercial banks in Indonesia.

Default by borrowers is the major contribution to the problems experienced by banks, associated with excessive credit exposure and weak asset-liabilities management. The credit default itself need not be a threat to the banks if the amount is not significant or the
banks have sound funding management so that they can manage their liquidity properly when the actual cash inflow fails to reach the amount projected. This condition normally emerges when liquidity in the economy is reduced, initiated by increasing interest rates. In these circumstances, those banks which have vulnerable liquidity will reduce the spread as a result of a lack of funding. Therefore, they offer high interest rates on deposits to attract investors, or ask for help from other group members to improve their liquidity. In Indonesia, some banks were coping with that problem by covering their liabilities from the clearing system by asking for lifeboat support from the central bank or other banks. Individual cases discussed above show that some banks were having financial problems because of loan losses or credit default, examples being Johnson Matthey Bankers in the UK, Banco Ambrosiano in Italy, Continental Illinois and Pennsylvania in the US, and Pertiwi, Maranu, Sampurna, Bapindo and Summa in Indonesia. The David Hale report for the G-7 council in Japan, 1991, outlined the loan problems faced by the G-7 member countries.

Losses on derivative and foreign exchange transactions were also major causes of failure. Such problems normally result from inexperience in these kinds of services and from weak internal controls. Sometimes a bank’s exposures break the limits that have been established for normal operations. Franklin National Bank (FNB) suffered large losses from foreign exchange operations. Bank Duta, one of the top 10 private banks in Indonesia, declared losses of $417 million from foreign exchange operations. The foreign exchange director was sent to jail because the court considered that he was dishonest in running the operation.

Fraud is also often a source of problems for the banks. BCCI is an example of a spectacular collapse because of fraud. Bank Duta in Indonesia gave a lesson to the supervisory authorities as well as to the public accountants in how to hide the true information by providing false accounting records. The supervisory authorities failed to detect the true condition of the bank because of illegal activities which were not recorded and internal controls in the bank which did not work properly.
Weakness in management was also one of the causes of these bank problems. As we know, there must be internal rules to govern operations and each level of management should understand and follow the rules. Weak management normally breaks its own rules for different reasons. Loan concentration limits were ignored by some banks; Bukopin and Bapindo are good examples of such cases in Indonesia. Bapindo suffered loan losses from a customer that accounted for 13.5 percent of the total credit portfolio and 140 percent of the bank's capital. This case was also one example where regulators could not prevent the losses from the beginning even though they knew that such practice was a potential problem for the bank.

Regulators are normally reluctant just to let the bank die without an attempt to save it. Bank Indonesia, as a central bank, is responsible for the stability of the banking system; therefore its policy of closing a bank is the last alternative and, because of this view, only Summa Bank was liquidated in the period of 1975-96. However, 16 banks were liquidated on 1 November 1997. The rest were taken over by other banks or investors. Sometimes, regulators use the term "too big to fail" as the main justification for rescuing the failed banks. Even in the US, there is a tendency to rescue banks through mergers. This sometimes creates additional problems because even if, in total, the banking system looks good, the basic problem still exists and the new management does not always succeed in cleaning up the problems.

Chapter 3 contains an empirical study concerning the determinants of problem banks in Indonesia by employing financial ratios which represent bank risks as discussed in this section.

1.7. Objectives of thesis

As noted above, 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 because depositors will loss their money. Additionally, the absence of deposit insurance will reduce public confidence to banking systems, increasing the possibility of bank runs.

More recently, some efforts have been made to improve the situation, such as the adoption of new approaches in supervising banks 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. The following section sets out the framework of this research (see Figure 1.5)

1.8. Framework of thesis

To achieve the objectives of this research, I adopt the following framework:
Based on the framework above, this research involves the following:

- Reviewing the theories of bank risks
- Identifying the determinants of bank risk in Indonesia by conducting an empirical study
- Reviewing the theories of capital adequacy regulation
- Outlining the capital adequacy proposals from the BIS (including the pros and cons)
- Designing alternative models for risk-based capital adequacy assessment using theories of finance and econometrics
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- Comparing capital requirements calculated using the BIS standardised methodology with alternative models.
- Explaining how an early warning system can be designed to assist bank supervisors in Indonesia

1.9. Structure of thesis

Chapter 1 (Introduction) outlines the background to banking problems in Indonesia, bank risk in theory and practice, bank failure in various countries, the aims and framework of this thesis, as well as providing a summary of each chapter (see below).

Chapter 2 discusses various empirical studies involving probability estimation of bank failure carried out by other authors.

Chapter 3 comprises an empirical study of the determinants of potential problem banks in Indonesia. This empirical study adopts limited dependent variables in regression analysis by employing "problem" and "non-problem" banks as dependent variables and financial ratios, which represent various bank risks, as independent variables. Using panel data of 240 banks from the fourth quarter of 1989 to the third quarter of 1995, this study finds that solvency risk, credit risk, liquidity risk, operational risk and interest rate risk were significant for most problem banks. However, foreign exchange rate risk was found to be insignificant, since few banks encountered financial problems because of foreign exchange rate exposure. However, some individual banks suffered illiquidity because of trading losses, such as Bank Duta and Bank Exim. As a result, further investigation of foreign exchange risk was conducted using one bank - the major player in Indonesia - as a case study. The empirical study in Chapter 5 provides evidence that the sample bank is sensitive to foreign exchange rate risk.
Chapter 4 provides an overview of capital adequacy assessment methodologies. This section consists of a discussion of the BIS's standardised methodology, internal models and the pre-commitment approach, including analysis of their the pros and cons.

Chapter 5 reviews the methodologies available for valuing positions in financial instruments. The aim of this chapter is to understand the basic concept of positions in financial instruments and to analyse valuation methods which can be used in the assessment of market risk.

Chapter 6 represents empirical work concerning the assessment of foreign exchange rate risk using alternative models. This empirical work involves forecasting the volatility of IDR exchange rates (Indonesian Rupiah) against 18 currencies using GARCH models and simulates these volatility estimates for foreign exchange positions of the largest banks in Indonesia. Using daily data from January 1996 to May 1997, the results show that the volatility estimates of IDR exchange rates are lower than suggested by risk weights in the BIS proposals (i.e. BIS suggests an 8% risk weight). However, the GARCH does not guarantee to provide volatility estimates of less than 8%, the results depend heavily on the time series data used in the models. Based on the back testing method, the maximum percentage error in GARCH (GARCH error occurs when the estimates are lower than actual) is 3.71% (see Table 6.6).

Chapter 7 draws conclusions from the evidence presented in the previous chapters. In particular, the empirical study in Chapter 3 shows that modelling of bank failure using a fixed effect logit model (Model 2) provides better results than the standard logit model (Model 1). This finding is significant contribution to the existing literature on the estimation of the probability of bank failure. Moreover, the results in this empirical study are reliable for two reasons: (1) the proportion of problem banks in the sample is around 40% (nearly in balance with the proportion of non-problem banks); (2) this study employs supervisory data (call reports). Furthermore, the empirical study in Chapter 6 finds that the decay factor of IDR exchange rate returns varies depending on the characteristics of the
data. This finding questions the assumption of J.P. Morgan that the decay factor is 0.94 for all currencies. Additionally, J.P. Morgan also suggests that the decay factor of 0.94 is similar to GARCH (1,1). This study finds that the characteristics of IDR exchange rate returns are not always GARCH (1,1). This finding further supports the evidence that the decay factor is not always 0.94. Finally, the empirical study in Chapter 6 also finds that the BIS’s approach suggests a higher volatility for IDR foreign exchange rates than that suggested by EWMA and GARCH, calling into question the validity of the former assumed risk weights.
Chapter 2

Survey of Empirical Works on Bank Failure

2.1. Introduction

Banks from around the world have failed due to a variety of causes. The signs of failure in traditional banks can often be detected at an early stage. Credit default is the major cause of failure in traditional banks. Symptoms of failure in modern banks may only appear shortly before the banks fail because trading in financial instruments and foreign exchange are the main activities of modern banks. This leaves bank supervisors with little time to take action to prevent bank failure. Therefore, identification of banks' condition prior to failure is crucial.

Assessment of bank failure is necessary for two reasons. First, an understanding of the determinants of bank failure will enable supervisors to supervise banks more efficiently, taking account of their risk profiles. Bank failure prediction models which employ independent variables that are significantly related to the risks causing failure can be used as a basis for calculating the risk of failure. Additionally, the results can be used to set variable rate deposit insurance premia. Second, the ability to differentiate between sound banks and troubled ones may allow bank supervisors to implement action to prevent problem banks from failing. In other words, the model can be used as early warning system in banking supervision.

Prediction of bank and corporate failures using limited dependent variables has been a popular area of research (see Altman, 1968, 1977; Meyer and Pifer, 1970; Deakin, 1972; Sinkey, 1975; Martin, 1977; Bovenzi, Marino and McFadden, 1983; Avery and Hanweck, 1984; Thomson, 1991; Espahbodi, 1991; Thomson, 1992; Heffernan, 1995).
Some researchers have adopted a linear form of multiple discriminant analysis (LMDA). However, this approach assumes that variance and co-variance matrices of independent variables are equal across groups, and that independent variables are multivariate normally distributed. The normal distribution assumption for independent variables is necessary to allow for significance tests on individual coefficients. An alternative model for assessing the probability of bank failure is a binary choice regression model. Many derivations of such binary choice models have been developed to estimate the probability of bank failure. This chapter discuss how to select the appropriate failure prediction model. However, the choice of model is not the only problem involved in predicting bank failure. Sometimes we may face data limitation problems. This is likely to be because the proportion of failed to sound banks is relatively small. Finally, these constraints may lead to prediction bias.

This chapter will review the literature on failure prediction (for both banks and companies), focusing on the models, data sets, variables, and testing methods used and the results derived. The chapter is organised in the following way: Section 2.2 outlines the aims of bank failure prediction models; Section 2.3 discusses modelling in the prediction of bank or company failure; Section 2.4 assesses the needs of sampling; Section 2.5 discusses the criteria of bank failure; 2.6 outlines the explanatory variables used in previous studies; Section 2.7 discusses the performance measurement and tests used; and Section 2.8 comprises the conclusions.

2.2. The aims of bank failure prediction models

The introductory section in this chapter mentions that the purposes of the probability estimations of bank failure are two-fold: (1) providing an early warning system in banking supervision; and (2) identifying the determinants of bank failure. This section will discuss these purposes in more detail.

Early identification of potential failure is necessary for regulatory agencies to ensure that corrective actions can be carried out promptly before the condition of banks deteriorates
towards failure. The failure of banks may affect the economy as a whole through the
deterioration of public confidence in the banking system and, furthermore, through
reduction in the nation’s money supply.

Bank failure estimation models can provide a tool for supervisory agencies to estimate the
probability of failure for each bank on a regular basis, such as monthly or quarterly.
Financial ratios, which may be updated every month or quarter, can be employed in the
model to obtain the probability of failure for each bank. If the probability figure breaks the
trigger (the cut-off point - see below), supervisory agencies will pay special attention to
the banks and suggest corrective action, if necessary, to reduce the probability of failure.
However, the selection of the cut-off point is arbitrary. Some studies adopt 0.5 as the
basis on which to decide whether a bank is classified as failed or sound. If the probability
estimate is >0.5, the bank will be classified as a failed bank and if the probability is <0.5,
the bank will be classified as a sound bank. However, many researchers argue that 0.5 is
not an appropriate cut-off point since the number of failed banks is not 50% of the total
sample. Adoption of the cut-off point of 0.5 for an extreme difference between the
number of failed banks and sound banks (e.g. 10% failed banks and 90% sound banks) will
create significance bias in the classification (Mandala, 1994). Many researchers adopt
Section 2.4 discusses in more detail the needs of sampling.

The ultimate purpose of predicting the probability of failure is to provide information for
bank supervisors concerning the causes of failure. The model employs several explanatory
variables which represent the various causes of failures. The determinants of failure can be
derived from significant variables in the model. However, the relationship between the
financial variables and bank failure must be statistically valid, otherwise the accuracy of the
estimates can be enhanced by employing as many independent variables as possible without
considering the statistical validity of the parameters. This type of regression is recognised
determinants of failure rather than early warning systems in her study.
2.3. Modelling in the prediction of bank or company failure

In the introductory section to this chapter, it was mentioned that there are two approaches which have been used in the prediction of bank or company failure; discriminant analysis and limited dependent variable regression models using maximum likelihood functions. This section discusses in more detail the pros and cons of these models.

This study ignores the linear probability model which has been used by Davis (1992) for two reasons. First, the model assumes that a company is considered a failed company if the profit maximisation yields a negative number. This assumption can be expressed in the following equation:

$$pF(L) - WL - qD + S < 0$$

where,

- $pF(L)$ = output function
- $WL$ = input function
- $qD$ = debt with q interest rate
- $S$ = the value of share after the deduction of $D$

The model is less applicable in the prediction of bank failure because banks may not fail in the real business world even though the result of profit maximisation is less than zero, as assumed in Davis's model. Because of asymmetric information in the banking industry, banks may still exist by raising new deposits or interbank call money when the profit maximisation given by the model above is negative. In some cases, banks can survive and be considered as sound banks after certain periods of time.

Second, in estimating the probability of bankruptcy, $\mu(.)$, Davis (1992) adopts the following equation:
\[ \mu(.) = \mu(W, PM, q, r, D, MV, \rho, \sigma, AD) \]

where,

- \( W \) = the price of labor
- \( PM \) = the price of raw material
- \( q \) = the real interest rate
- \( r \) = the nominal interest rate
- \( D \) = the debt
- \( \rho \) = the output price
- \( \sigma \) = the variance of the output price
- \( AD \) = the aggregate demand

This approach can be identified as a linear probability model (LPM) which is not applicable to this study. The ensuing discussion in this section contains the reasons for not using the LPM.

Discriminant analysis is an approach used to classify banks or companies in a certain manner such as “failed” and “sound”. This approach has been widely used in the prediction of bank failure (see Altman, 1968, 1977; Sinkey, 1975; and Martin, 1977). However, this approach employs some assumptions which violate real-world conditions. By simplifying reality, application of this approach in the economics, finance and business literature can only have limited usefulness. The key assumptions in discriminant analysis include the following (Hubert, 1994): (1) The standard discriminant analysis procedures assume that variables used to describe or characterise the members of the groups being investigated are multivariate normally distributed. In fact, this is very rare in practice. Violations of the normality assumption may affect the validity of the significance parameters and estimated error rate tests. Employing the normality assumption and applying the standard procedures of discriminant analysis can, at best, produce only reasonable approximations to the truth. (2) The standard discriminant analysis also assumes that the group dispersion (variance-
covariance) matrices are equal across groups. Violation of this assumption will affect the significance test for the differences in group means and classification rules. (3) Discriminant analysis procedures assume that the groups being investigated are discrete and identifiable. In fact, the definition of bank failure is based on arbitrary judgements.

Haslem and Longbrake (1971) grouped banks based upon the distribution of their profitability. Sinkey (1975) distinguished between “problem” and “non-problem” banks using guidelines which were used by the Federal Deposit Insurance Corporation (FDIC). Based on these guidelines, the FDIC keeps a list of problem banks and updates this constantly to keep its eyes on the banks which are most likely to need special attention from supervisors. Inconsistency in the application of the criteria used to identify “problem” and “non-problem” (or “failed” and “non-failed”) banks will lead to biased probability estimates. Additionally, discriminating factors in discriminant analysis are calculated just for the purposes of classifying groups, not for determining the causes of failure. Therefore, this approach is not suitable for determining the probability of bank failure.

Realising the limitation of discriminant analysis, Mayer and Pifer (1970) adopted a limited dependent variable regression model in their study. This approach employs a binary choice of dependent variables which gives the symbol “1” for failed banks and “0” for non-failed (ie. sound) banks. Econometricians identify this model as a linear probability model (LPM). However, this approach does not guarantee that the estimates will fall in the range between 1 and 0 (Gujarati, 1995, p.554). To ensure that the estimates fall between 1 and 0 we have to impose a restriction on the regression estimates.

The logistic approach can be applied to LPM (Aldric and Nelson, 1984, p.48 and Mandala, 1994, pp.23-6) as an alternative way to ensure that the estimates fall between 0 and 1. In mathematical terms, this can be explained in the following equation:

\[ y_i = \beta_1 + \beta_k \sum_{i=1}^{N} x_{ik} + e_i \]  

(2.1)
where,

\( y_i \) = independent variable of observation \( i \) (symbol "1" for failed and "0" for non-failed)

\( \beta_0 \) = intercept

\( \beta_k \) = coefficient of the \( k^{th} \) independent variable

\( x_k \) = independent variable \( k \) \( (k = 1,2,3,........k) \)

\( e_i \) = error term for observation \( i \)

The errors in the equation above are identically identified as following a normal distribution or i.i.d. \( \text{N}(0,\sigma^2) \).

From equation 2.1, we can get the list of un-constrained probability estimates \( (z_i) \).

Assuming \( P_i \) is the probability that a bank is classified as "failed" and \( P(=1-P_i) \) is the probability that a bank is classified as "non-failed", the logistic function can be shown as follows:

\[
\ln \frac{P_i}{1-P_i} = z_i
\]

With algebraic manipulation, we can solve for \( P_i \) using the following equation:

\[
P_i = \frac{e^{z_i}}{1 + e^{z_i}} \quad (2.2)
\]

The coefficients of independent variables can be derived using the maximum likelihood approach.

With the logistic treatment, the probability will be bounded by 0 and 1. The graph below shows the probability distribution using a logistic function.
Logit models have been widely used in the prediction of bank failure (Martin, 1977; Thomson, 1991, Espahdobi, 1991). They are preferable to discriminant analysis because of superior statistical properties which affect the t-test for significance parameters, the log likelihood ratio test for insignificant parameters and the Pseudo-R square for the goodness of fit, and because the discriminant analysis relies upon assumptions which do not exist in reality. This has lead a growing number of researchers to employ logit models in the prediction of bank or company failure.

The standard logit model is normally applied to cross sectional data. If we apply a standard logit model to cross sectional and time series data (i.e. panel data), we must implicitly assume that the coefficients of the explanatory variables are the same over time and between cross sectional units. In mathematical form, this can be shown in the following equation:

\[ y_{it} = \beta_0 + \beta_k \sum_{k=1}^{K} \sum_{t=1}^{T} x_{kt} + e_{it} \]  

(2.3)
Chapter 2 - Survey of Empirical Works on Bank Failure

where,

\[ y_{it} = \text{dependent variable of cross section } i \text{ and time } t \]
\[ \beta_i = \text{intercept for all cross section } i \text{ and time } t \]
\[ x_{kit} = k^{th} \text{ independent variable for cross section } i \text{ and time } t \]
\[ \beta_k = \text{coefficient of independent variable } k \text{ for all cross section } i \text{ and time } t \]
\[ e_{it} = \text{disturbance of cross section } i \text{ and time } t \]

Similarly to equation 2.1, equation 2.3 also assumes that \( e_{it} \) is i.i.d. \( N(0, \sigma^2) \).

Equation 2.3 assumes that the coefficients of parameters are the same for all cross sectional units and over time. However, this assumption is not always valid. To accommodate the individual and time series effects, we can employ the following equation:

\[
y_{it} = \beta_{it} + \sum_{k=1}^{K} \sum_{t=1}^{T} x_{kit} + e_{it} \quad (2.4)
\]

Since we have only a small number of cross sectional units and a short time series, applying this model will be very simple. It is similar to running regressions simultaneously on cross sectional units and time series. However, this model becomes more complicated for a large number of cross sectional units and long time series.

To simplify this problem, Chamberlain (1980) proposed the use of the following alternatives: a fixed-effect model that maximises the joint likelihood function; or a fixed-effect model with a conditional likelihood function. The joint likelihood function fixed-effect model assumes that: (1) observations across groups are independent; (2) observations within a group are independent as well, but conditional on the group effects. The dependence of different observations within a group is assumed to be due to their common dependence on the group specific effect, \( \beta_i \). In fact, a more general form of independence is possible, such as serial correlation. Therefore, the regression in this model is simply a multiple regression of \( y \) on \( x \) and a set of a group indicators which is represented by a dummy variable. Then, the likelihood function can be processed using the
normal procedure. Chapter 3 shows in detail how to solve the regression using the maximum likelihood function.

Chamberlain also suggests adopting a conditional likelihood function fixed-effect model. The key idea is to base the likelihood function on the conditional distribution of the data.

Then, we can say that the statistic of the fixed-effect ($\beta_i$) is $\sum_i y_i$. Chamberlain looks at the case of $T = 2$. If $y_{i1} + y_{i2} = 0$ or 2, then $y_{i1}$ and $y_{i2}$ can be determined using their sum. However, if $y_{i1} + y_{i2} = 1$, two possibilities may occur for the order of $y_{i1}$ and $y_{i2}$. The first event ($w_i = 0$) arises if $(y_{i1}, y_{i2}) = (0, 1)$, and the second event ($w_i = 1$) arises if $(y_{i1}, y_{i2}) = (1, 0)$. The conditional density is given by the following:

$$\text{prob} \left( w_i = 1 | y_{i1} + y_{i2} = 1 \right) = \frac{\text{prob} \left( w_i = 1 \right)}{\text{prob} \left( w_i = 0 \right) + \text{prob} \left( w_i = 1 \right)} = \frac{e^{\beta(x_{i2} - x_{i1})}}{1 + e^{\beta(x_{i2} - x_{i1})}} = F[\beta' (x_{i2} - x_{i1})] \quad (2.5)$$

Then, the conditional log-likelihood function is:

$$L = \sum_{i \in I} \{w_i \ln F[\beta' (x_{i2} - x_{i1})] + (1 - w_i) \ln F[-\beta' (x_{i2} - x_{i1})] \},$$

where,

$I_1 = \{i | y_{i1} + y_{i2} = 1 \}$

Heffernan (1995) adopts the conditional logit fixed-effect model to run panel data of bank failures from an international pool and a Scandinavian pool. However, the conditional logit fixed-effect model suffers from computational problems. According to Green (1995), the maximum of the series ($T$) is 10. Computation in conditional logit fixed-effect models will become prohibitive when $T > 10$ in the log likelihood function. The reason is that the
larger the value of $T$ in the log likelihood function the larger the space required, and computation is required at a geometric rate.

Many variations on the standard logit model have been used in the prediction of bank failure. Thomson (1992) extends the standard logit model into a two-step logit model. Although, the model is similar to the standard logit model, the two step logit model employs an ordinary least square (OLS) regression to estimate one or more independent variables before running the logit regression. The drawback of this approach is that it requires the separation of the equation into at least two equations. This produces errors in each equation. Classification error analysis only appears in logit models (ignoring errors in other OLS equations). Error estimates do not represent the overall errors in the models, and the result will be misleading. For this reason, I believe a single equation model is preferable.

Some researchers have employed probit models to predict bank or company failure (Bovenzi, et al, 1983; Casey, et al, 1986; Pastena and Ruland, 1986; and Dopuch, et al, 1987). The difference between probit and logit models lies in the treatment adopted to ensure that the probability estimates will fall in the range between 0 and 1. Unbounded results (i.e. unlimited range of probability) are useless in determining the probability estimates. Logit models adopt a logistic probability distribution function while probit models adopt a normal probability distribution function. In mathematical terms, we can show the general form of a normal distribution for observations with mean $\mu$ and $\sigma^2$ in the following equation (Green, 1993, p.58):

$$f(x|\mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

(2.6)

Probit and logit models are alike because the normal and logistic distributions are similarly shaped. The difference lies just in the tails. Many studies have been done to compare these models (see, Aldrich and Nelson, 1984, Martin, 1977). The results show that probit and
logit models yield similar probability estimates. However, the logit model is computationally simpler and more tractable than the probit model.

2.4. Sample proportion

Models to predict bank failure may be constrained by a limited number of observations on bank failure. A relatively small number of bank failures in the observations will yield unreliable results. Previous studies show that the lower the percentage of failure observations in a given sample, the higher the percentage of “correct” classifications produced. A good model will give stable results whatever the number of failure observations in the sample. The following table shows the link between the proportion of failed bank observations and the number of correct classifications produced in estimation.
Table 2.1.

Relationship between the number of bank failure observations and the number of correct classifications produced in the modelling of bank failures

<table>
<thead>
<tr>
<th>Models and number of parameters</th>
<th>Number of failed banks</th>
<th>% from total sample</th>
<th>% of observations correctly classified</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Bovenzi et al (1983) - 7 parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-call report 2 year lead time</td>
<td>3,000</td>
<td>21</td>
<td>79</td>
</tr>
<tr>
<td>-call report 2 year lead time</td>
<td>1,000</td>
<td>7</td>
<td>93</td>
</tr>
<tr>
<td>-call report 2 year lead time</td>
<td>600</td>
<td>4</td>
<td>96</td>
</tr>
<tr>
<td>-call report 1 year lead time</td>
<td>3,000</td>
<td>21</td>
<td>79</td>
</tr>
<tr>
<td>-call report 1 year lead time</td>
<td>2,000</td>
<td>14</td>
<td>86</td>
</tr>
<tr>
<td>-call report 1 year lead time</td>
<td>1,000</td>
<td>7</td>
<td>93</td>
</tr>
<tr>
<td>-examination report 2 year lead time</td>
<td>3,000</td>
<td>21</td>
<td>79</td>
</tr>
<tr>
<td>-examination report 2 year lead time</td>
<td>1,000</td>
<td>7</td>
<td>93</td>
</tr>
<tr>
<td>-examination report 2 year lead time</td>
<td>600</td>
<td>4</td>
<td>96</td>
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<tr>
<td>-examination report 1 year lead time</td>
<td>3,000</td>
<td>21</td>
<td>79</td>
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<tr>
<td>-examination report 1 year lead time</td>
<td>2,000</td>
<td>14</td>
<td>86</td>
</tr>
<tr>
<td>-examination report 1 year lead time</td>
<td>1,000</td>
<td>7</td>
<td>93</td>
</tr>
<tr>
<td>2. Korobow-Stuhr (1983) - 6 parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 year lead time</td>
<td>31</td>
<td>20</td>
<td>84</td>
</tr>
<tr>
<td>16</td>
<td>10</td>
<td>94</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>98</td>
<td></td>
</tr>
<tr>
<td>3. Martin (1977 - 9 parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 year lead time</td>
<td>517</td>
<td>9</td>
<td>91</td>
</tr>
<tr>
<td>4. Sinkey (1975) - 11 parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>classification model</td>
<td>94</td>
<td>46</td>
<td>82</td>
</tr>
<tr>
<td>5. Espahbodi (1991) - 13 parameters</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 year lead time</td>
<td>29</td>
<td>76</td>
<td>75.71</td>
</tr>
<tr>
<td>1 year lead time</td>
<td>33</td>
<td>89</td>
<td>87.62</td>
</tr>
<tr>
<td>1984 data</td>
<td>78</td>
<td>4.49</td>
<td>86.17</td>
</tr>
<tr>
<td>1986 data</td>
<td>33</td>
<td>7.66</td>
<td>88.212</td>
</tr>
<tr>
<td>1988 data</td>
<td>174</td>
<td>10.02</td>
<td>93.988</td>
</tr>
</tbody>
</table>

The studies cited above use the percentage of correct classifications as a measure of the performance of the models. A perfect model will estimate 100 percent of observations correctly. However, the proportion of failed and sound banks in the sample affect the classification results. The table above shows that a lower percentage of failed bank observations is associated with a higher percentage of banks being classified correctly. Since the models employ failed and non-failed banks as dependent variables, the number of failed banks will be very low as a result of governments’ efforts to prevent banks from
failing. Therefore, the finding that a high percentage of banks are classified correctly by a model which employs a low percentage of failed banks in samples does not reflect the true reliability of the model. In an extreme case, we cannot say that the model is reliable when there are only 1 observation of bank failure and 100 observations of sound banks in a sample. The more observations of bank failure included in a sample, the more we can reliably assess the performance of the model. The model is perfect when the correct classification remains constant whatever the number of bank failure in the sample. The percentage of failed and non-failed banks in a sample plays a critical role in determining the usefulness of the model.

### 2.5. Criteria for classifying banks as “failures”

The definition of “failure” will play an important role in determining the number of banks put into this group. In general, a bank is categorised as a “failure” if the bank cannot carry on its operations without incurring losses which will immediately result in negative net worth. This definition has been used by several authors to predict bank failure, such as Meyer (1970) and Thomson (1991, 1992). However, some banks do not fail, as a result of governments' intervention to prevent them from failing. Therefore, the number of bank failures in reality is very low. A large gap in sample proportions between “failed” and “non-failed” banks will thus bias the “performance” of the model. To obtain a reasonable number of bank failures, several researchers have thus defined bank failure using wider definition of failure. Martin (1977), for example, classifies a bank as a failure if one of the following holds: the occurrence of failure, supervisory merger, and/or emergency measures to resolve an imminent failure situation. Other authors adopt different definitions of “failure”. In Heffernan’s study (1995), a bank is considered as a “failure” if at least one of the following conditions holds: the bank is liquidated, taken over under government supervision, and/or rescued with a package which includes state financial support. Thomson (1991, 1992), meanwhile, includes mergers with FDIC assistance as an additional criteria of bank failure, extending the definition used by Heffernan.
Another approach to determining bank failure is to use the supervisory agency’s judgement of bank condition, rather than actual failure. Each agency maintains a “problem list” of banks which are considered substantially riskier than other banks and which will require corrective action by management. Sinkey (1975) adopts definitions for “problem” and “non-problem” banks based on the FDIC’s approach. The FDIC used three classifications for problem banks: (1) the “Serious problem-potential payoff” (PPO) label is designed to identify in advance a bank facing serious problems and which has at least a fifty percent chance of requiring FDIC financial assistance in the near future; (2) the “Serious problem” (SP) label is designed to indicate a banking situation that threatens ultimately to involve the FDIC in financial outlay unless drastic changes occur; (3) and the “Other problem” (OP) label is designed to define a banking situation involving a significant weakness, but with a lesser degree of vulnerability than cases (1) or (2) above, but still calling for aggressive supervision or attention by the FDIC. The FDIC is concerned with the evaluation of risk exposure, and believes that problem banks face greater risks than non-problem banks.

Classification of “problem” and “non-problem” banks in this ways depends very much on the subjective judgement of bank supervisors. Different agencies often differ in their opinions on whether a bank is a “problem”. However, if such a problem bank classification is followed by actual failure, a model using “problem” and “non-problem” banks defined in this way may provide a longer lead time for corrective action than would a model based on actual failure because “problem” in this case is the condition before banks failed.

The adoption of bank condition prior to failure will be useful in the operation of an early warning system in banking supervision. This approach can be designed in such a way as to be an additional tool in bank examination and supervision. The advantages of using “problem” and “non-problem” banks defined in this way as dependent variables are as follows; (1) More efficient allocation of resources in banking supervision. Early identification of problem banks will help bank supervision agencies to allocate resources
based on need. Less time and fewer resources will be spent on non-problem banks rather than on problem banks. Examination frequency may also be reduced for non-problem banks. (2) The results of this approach can be used as a basis for evaluation of the examination and supervisory performance of banking supervision (i.e. the supervisory performance is not good if many banks are classified as problems). (3) This approach can be used to provide a basis for assessing deposit-insurance premiums based on the probability of suffering problems. (4) It provides an objective methodology for assessing bank condition prior to failure. Although bank regulatory agencies may employ composite ratings to reflect the condition of banks, the components of the composite rating reflect, in turn, the subjective judgements of bank supervisors. (5) It may provide sufficient time to allow for corrective action to prevent banks from failing.

For the above reasons, Sinkey (1975) adopts “problem” and “non-problem” banks as classified according to FDIC guidelines in his studies. However, the adoption of this approach to classifying “problem” and “non-problem” banks suffers from the following drawbacks: (1) the definition of “problem” and “non-problem” may vary between supervisory agencies; (2) the criteria used to define problem banks may change due to changes in regulations and/or the judgement of supervisors. Inconsistency in defining problem banks leads to the provision of unreliable estimates by the model.

2.6. Explanatory variables

Financial ratios are the main explanatory variables used to estimate the probability of failure. The ratios normally represent liquidity, solvency, size, asset quality, and earnings. Most of the previous authors surveyed above believe that such variables can be used to represent the causes of bank failure. However, due to the development of risk analysis, the causes of bank failure can now be more closely identified as arising from such risk as credit risk, operational risk, foreign exchange risk, interest rate risk, credit risk, and fraud risk. These risks will affect the liquidity and solvency of banks. Some previous researchers did
not include the ratios which represent foreign exchange and interest rate risk. Table 2.2 shows in detail the variables which have been used in previous studies.

Previous researchers also employed different numbers of variables. Some of them employed a small number of independent variables while others employed a large number. The number of explanatory variables affects the goodness-of-fit in prediction. The more explanatory variables that are included in the regression, the better the goodness-of-fit of the regression. However, goodness-of-fit in regressions which employ too many explanatory variables may be because of multicollinearity between independent variables - these regressions are called spurious regressions (Granger and Newbold, 1974).
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Working capital/total assets</td>
<td>Error in predicting cash and securities/total assets</td>
<td>Net income/total assets</td>
<td>Loans and leases to total sources of funds</td>
<td>Asset quality (ratio of classified and special mentioned assets to bank capital)</td>
<td>Book equity capital plus the reserve for loan and lease losses minus the sum of loans 90 days past due but still accruing and non-accruing loans/total assets</td>
<td>Cash+US Treasury Securities/assets</td>
<td>Natural logarithm of total bank assets less loan loss reserve allowance to (TA)</td>
<td>Earning assets (average)</td>
</tr>
<tr>
<td>2</td>
<td>Retained earnings/total assets</td>
<td>Coefficient of variation in rate of interest on time deposits</td>
<td>Gross charge-off/net operating income</td>
<td>Equity capital to adjusted risk assets</td>
<td>Capital to assets ratio</td>
<td>Net charge-offs/total loans</td>
<td>Loans/assets</td>
<td>Ratio of net after-tax income to TA</td>
<td>Net interest income/average earning assets</td>
</tr>
<tr>
<td>3</td>
<td>Earnings before interest and taxes/total assets</td>
<td>Time/demand deposit ratio</td>
<td>Expenses/operating revenue</td>
<td>Operating expenses to operating revenues</td>
<td>Operating income to assets ratio</td>
<td>Loan portfolio based on Herfindahl index</td>
<td>Provision for loan losses/operating expenses</td>
<td>Ratio of equity capital plus loan loss reserve allowances to TA</td>
<td>Non-interest income/average assets</td>
</tr>
<tr>
<td>4</td>
<td>Market value equity/book value of total debt</td>
<td>Operating revenue/operating costs</td>
<td>Loans/total assets</td>
<td>Gross charge-offs to net income plus provisions for loan losses</td>
<td>Debt to equity ratio</td>
<td>Net loans and leases/total assets</td>
<td>Loans/(capital + reserves)</td>
<td>Ratio of net loans (total loans less loan loss reserve allowances) to TA</td>
<td>Non-interest expenses/average assets</td>
</tr>
<tr>
<td>5</td>
<td>Sales/total assets</td>
<td>Operating income/total assets</td>
<td>Commercial loans/total loans</td>
<td>Assets size of bank</td>
<td>Non-deposit liabilities/cash and investment securities</td>
<td>Operating expenses/operating income</td>
<td>Ratio of net loan charge-offs (gross loan charge-offs less recoveries) to net loans</td>
<td>Equity/total assets</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.2
Independent Variables Used in the Prediction of Bank Failure
### Table 2.2 (continued)

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<tbody>
<tr>
<td>6.</td>
<td>-</td>
<td>Growth of consumer loans /total assets</td>
<td>Loss provision /loans + securities</td>
<td>Net occupancy expenses to net income</td>
<td>Overheads/total assets</td>
<td>Loan revenue /total revenue</td>
<td>US Treasury Securities revenue/total revenue</td>
<td>Ratio of commercial and industrial loans to net loans</td>
<td>Dividends/net income</td>
</tr>
<tr>
<td>7.</td>
<td>-</td>
<td>Growth of cash and securities/total assets</td>
<td>Net liquid assets/total assets</td>
<td>-</td>
<td>Loans to total assets</td>
<td>Net income after taxes /total assets</td>
<td></td>
<td>Rate of US government and agency securities plus cash items in process of collection, vault cash and reserves at Federal Reserve Banks to total assets</td>
<td>Average liquid assets /average assets</td>
</tr>
<tr>
<td>8.</td>
<td>-</td>
<td>Coefficient of variation of total loans</td>
<td>Gross capital/risk assets</td>
<td>-</td>
<td>Loans to insiders/total assets</td>
<td>State &amp; local obligation revenue /total revenue</td>
<td></td>
<td>Percentage change in total deposits within each bank's local banking market (an SMSA or non-SMSA county of the bank's home office) The Herfindahl index (the sum of squares of market shares for banking organisations) for each bank's local banking market</td>
<td>Average loans /average assets</td>
</tr>
<tr>
<td>9.</td>
<td>-</td>
<td>Real estate loans/total assets</td>
<td>-</td>
<td>-</td>
<td>Dummy variable for holding company</td>
<td>Interest paid on deposits /total revenue</td>
<td></td>
<td></td>
<td>Average deposits /average assets</td>
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Table 2.2 (continued)

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<tr>
<td>10.</td>
<td>-</td>
<td>Fixed assets/total assets</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Natural logarithm of total assets</td>
<td>Other expenses/ total revenue</td>
<td>-</td>
<td>Non-performing assets /total loans &amp; OREO Reserves /total loans</td>
</tr>
<tr>
<td>11.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Natural logarithm of average deposits per banking office</td>
<td>-</td>
<td>-</td>
<td>Net charge-offs /average loans</td>
</tr>
<tr>
<td>12.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Output Herfindahl index constructed using state level gross domestic output by one digit SIC codes</td>
<td>-</td>
<td>-</td>
<td>Recoveries /gross charge-offs</td>
</tr>
<tr>
<td>13.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Unemployment rate in the county where the bank is headquartered</td>
<td>-</td>
<td>-</td>
<td>USD assets /total USD assets</td>
</tr>
<tr>
<td>14.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Percent change in state-level personal income</td>
<td>-</td>
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<td>USD assets</td>
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<td>15.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Dun and Bradstreet’s state-level small-business failure rate per 10,000 concerns</td>
<td>-</td>
<td>-</td>
<td>USD assets</td>
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## Table 2.2 (continued)

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<td>16.</td>
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<td>-</td>
<td>-</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>USD assets /US nominal GDP</td>
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<td></td>
<td></td>
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<td>Log ASSGDP (log assets in USD/US nominal GDP)</td>
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<td>17.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td>-</td>
<td>Average annual nominal (INT) or real (RINT) interest rate:annual average computed from monthly money market rate</td>
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<td>18.</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>Annual inflation rate</td>
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<td>19.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td>-</td>
<td>-</td>
<td>Annual consumer price index</td>
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<td>20.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Annual real GDP growth rate</td>
</tr>
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<td>21.</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>IBCA rating for bank</td>
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<td>22.</td>
<td>-</td>
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</table>
2.7. Performance measurement and tests

2.7.1. T-test

There are many approaches available to test the results of the logit models with maximum likelihood estimation. This study uses the t-test to examine the coefficients of parameters individually by employing the null hypothesis that the coefficient of an individual parameter is zero. According to Pindyck (1991, p.281), the t-test may be applied in maximum likelihood estimation since all parameter estimators are known to be (asymptotically) normal. The t-value is derived from:

\[
\frac{(\beta - \beta_0)}{se_{\beta}}
\]  

(2.7)

where se stands for standard error of estimates. By using t-tables, we can reject or accept the hypothesis with a certain degree of confidence. If the results show that some variables have zero coefficients, the test will continue by employing a log likelihood ratio test to test whether the coefficients of parameters remain zero when they interact simultaneously in the equation.

2.7.2. Log likelihood ratio test

To measure the goodness of fit, this study employs the likelihood ratio test by transforming the restricted log likelihood function (RLLF) and the unrestricted log likelihood function (ULLF) into the following formula, (Gujarati, 1995, p.281, Aldrich and Nelson, 1984, p.54, Green, 1993, p.647):

\[
\lambda = 2(UULF - RLLF)
\]  

(2.8)
ULLF is the log likelihood of the original regression (i.e. without any restriction) while RLLF is the result of the log likelihood of regression with the priori that one or some of the parameter coefficients are zero. The value of $\lambda$ will follow the chi-square ($\chi^2$) distribution with a degree of freedom equal to the number of parameters restricted to zero. The test accepts the hypothesis if there is no difference between ULLF and RLLF (i.e. $\lambda = 0$) and rejects otherwise. Alternatively, for $\lambda \neq 0$, the test can be performed by comparing the value of $\lambda$ and the value of the chi-square distribution. Based on the chi-square distribution table, we can identify whether the hypothesis is accepted using a certain level of confidence and degree of freedom.

2.7.3. Pseudo-$R^2$

To measure the performance of model predictions, previous studies have used pseudo-$R^2$ and classification errors. Traditional $R^2$ is not appropriate for models with a limited dependent variable (Aldrich and Nelson, 1984, p.56) as the value of the dependent variable is 0 or 1. The criteria of success in the traditional $R^2$ estimation is the degree to which the error of variance is minimised, while the logit model uses the criterion of maximum likelihood.

Previous researchers have used several methods to measure pseudo $R^2$. Several surveys, such as those by McFadden (1973, p.121), Aldrich and Nelson (1984) and McKelvey and Zavoina, (1975) indicate that different pseudo $R^2$'s yield different values for the same model and data. To identify which one is the best is arbitrary. Zimmermann (1996, pp.241-59) suggests that the McKelvey and Zavoina $R^2$'s model ($R^2_{MZ}$) yields the best score. However, the $R^2_{MZ}$ produces a score which is more sensitive to misspecification in the error term than the McFadden approach, especially in binary probit and logit models. For the purpose of this study, we will use McFadden's pseudo $R^2$. The detail of the mathematical expression of the pseudo $R^2$ is shown in Appendix 2.1.
2.7.4. Classification of errors

Previous studies also examined the power of the regressions to predict the probability of problem banks emerging by using all observations. The result of these prediction models is an array of probability numbers between 0 and 1. By employing a given cut-off point, this model produces estimates in three categories: “correct” estimates, “error I type” estimates and “error II type” estimates. A cut-off point is the point used to determine whether a bank is classified as a problem or a non-problem bank. This approach has been widely used by authors in estimating the probability of bank or company failure (Martin, 1977; Sinkey, 1975; Bovenzi, Marino and McFadden, 1983; Korobow and Stuhr, 1983; Espahbodi, 1991). For instance, a cut-off point of 0.4 means that the models identify estimated values of > 0.4 as problem banks and estimated values of < 0.4 as non-problem banks. The models produce correct estimates when the observations of problem banks are estimated as problems or, with a cut-off point of 0.4, the estimate value is >0.4. Error I types occur when the models predict non-problem banks as problems or, in this example, the models produce a probability >0.4 for a non-problem bank. Error II types occur when the models produce a probability of < 0.4 for a problem bank.

Details of this error scenario are shown in Table 2.3. The lower the cut-off point, the greater is the number of banks predicted as problems and the smaller the number of banks predicted as non-problems. The choice of a cut-off-point plays an important role in the calculation of errors. Therefore, a “fair” cut-off-point is important in error analysis. The sample proportion of failed and non-failed banks is believed to be the best criterion to determine the cut-off-point (Thomson, 1992). For instance, samples with 50% of failed banks and 50% of non-failed banks will use a cut-off point of 0.5, and samples with 60% of failed banks and 40% of non-failed banks will use a cut-off-point of 0.4.
<table>
<thead>
<tr>
<th>Table 2.3 Errors of Estimates</th>
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<tbody>
<tr>
<td><strong>Cut-off point 0.50</strong></td>
</tr>
<tr>
<td><strong>50/60</strong></td>
</tr>
<tr>
<td><strong>25/75</strong></td>
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</table>

Note:
- A cut-off point of 0.40 means that a bank is estimated as a problem when the probability of estimate is > 0.40.
- Error I type occurs when the model estimates an observation as a problem bank, but the observation is not a problem bank.
- Error II type occurs when the model estimates an observation as a non-problem bank, but the observation is a problem bank.
There is an argument that good results in error classification tests using within sample observations are not reliable because the observations which are employed to test the models were also used to generate the coefficient of parameters in regression. Therefore, out of sample tests are carried out in this study.

2.8. Conclusions

This study concludes that the logit model is to be preferred to the alternatives available because of its superior statistical properties. Although the probit model would give similar results, the logit model is mathematically more simple and tractable. LPM may produce estimated probabilities outside of the meaningful 0 and 1 range. LMDA may yield unreliable results since the multivariate normality assumption of discriminating factors and equal dispersion (variance-covariance) of each group do not exist. Although Martin (1977) maintains that discriminant analysis will provide similar results to that of the logit model, since the basic assumptions in discriminant analysis are satisfied, the probit and logit models are preferable because the significance of the independent variables can be tested more easily using the t statistic, and because many other statistical properties are readily available for analysis in this model, such as the log likelihood ratio test for insignificant parameters and the Pseudo-$R^2$ for the goodness-of-fit.

The prediction of the probability of banks becoming problems is more useful in banking supervision than the prediction of the probability of bank failure as it may provide sufficient time for the supervisory authorities to prevent banks from failing. Sinkey (1975), therefore, uses “problem” and “non-problem” banks as dependent variables in his study.

This study thus employs a logit probability model to contribute to the literature on the prediction of problem banks (based on the condition prior to failure) by focusing on the following points: (1) lowering the gap between the proportion of “problem” and “non-
problem” banks in observations to ensure that the results are reliable; (2) determining bank risks in Indonesia by employing independent variables which represent the various risks run by banks; and (3) employing a logit fixed-effect model using panel data of call reports to obtain group-effect (i.e. call report is financial data of banks in Indonesia which are intended just for bank supervisors in Bank Indonesia and are not available for public). Therefore, the results of this study will be reliable for determining of bank risk in Indonesia and early warning system in banking supervision.
Chapter 3

An Empirical Study of the Determinants of Potential Problem Banks in Indonesia

3.1. Introduction

The various sources of problems causing bank failures in selected countries have been discussed in detail in the introductory chapter (Chapter 1). This chapter will address the sources of the problems which can lead to bank failure in Indonesia using quantitative analysis. The aim of this empirical work is to identify bank risks, which are represented by explanatory variables within the regressions, in Indonesia. Moreover, the results of this study can be used as an additional early warning signal in banking supervision. [Detailed discussion concerning the needs of an early warning system is included in Chapter 1].

Based on the discussion in Chapter 2, this study finds that: (1) a standard logit model is not applicable for panel data; (2) a relatively small number of bank failures in samples will produce unreliable results; (3) independent variables used in the previous studies were not related directly to risks in banks; (4) prediction of bank condition prior to failure may provide a longer lead time for corrective action than prediction of bank failure.

The empirical study in this chapter contributes to the literature on failure prediction models by focusing on the following points: (1) employing a logit fixed-effect model to estimate the probability of banks becoming problem in Indonesia using panel data; (2) employing a relatively large number of problem banks in samples (i.e. 41.32%); (3) employing the condition of banks prior to failure (problem); (4) employing financial ratios which represent risks in banks; (5) employing supervisory data and information.

Chapter 3 is organised as follows: Section 3.2 outlines the models; Section 3.3 describes the data; Section 3.4 describes the dependent variables; Section 3.5 describes the
explanatory variables; Section 3.6 discusses the results of the empirical study; Section 3.7 summarises the conclusions drawn.

3.2. Models

There are some quantitative models (e.g. Discriminant analysis, LPM, Logit and Probit) which have been widely used to determine the causes of company failure by taking the fact whether or not a firm goes bankrupt as the dependent variable and financial ratios as the independent variables. After reviewing those models, Chapter 2 concludes that a logit model is the most appropriate one for this study. The main reason for choosing the logit model is the superior statistical properties of the model. However, a modified model is necessary to ensure that the coefficients of parameters are valid due to the existence of group effects in the panel data. The following part of this section develops the quantitative expression of the standard logit model for panel data.

The logit models involve the calculation of the probability distributions for dependent variables based on the cumulative logistic distribution function, as shown below. Intercept and constant coefficients are calculated by using the maximum likelihood method (ML). This approach estimates intercept and constant coefficients in such a way that the probability of observing the value of the $y$'s (dependent variables) is as high as possible up to the true values.

This study employs a binary dependent variable ($y$) where $y = 1$ for problem banks and $y = 0$ for non-problem banks. The value of $y$ is assumed to depend on the constant $\beta_1$ and the explanatory variables $x_i = (i = 1, 2, \ldots, i)$, and the coefficients of parameters are assumed to be the same for cross sectional units and over time. In mathematical terms, we can show this in the following equation:
\[ y_{it} = \beta_1 + \sum \beta_k x_{kit} + e_{it} \]  

where  
\[ i = 1, 2, \ldots, N, \]  
\[ e_{it} = \rho e_{i, t-1} + v_{it} \]  
\[ E[v_{it}] = 0, E[v_{it} v_{jt}] = \sigma_y, \text{ and } E[v_{it} v_{jt}] = 0 \text{ for } t \neq s \]  
\[ y_{it} = \text{the independent variable of an individual } i \text{ at time } t \]  
\[ \beta_1 = \text{the intercept} \]  
\[ \beta_k = \text{the slope coefficient of parameter } x_{kit} \]  
\[ x_{kit} = \text{the } k^{th} \text{ independent variable of an individual } i \text{ at time } t \]  
\[ e_{it} = \text{disturbance term of an individual } i \text{ at time } t \]  

Assume \( P_i \) is the probability that a bank is classified as a problem and \( P(=1-P_i) \) is the probability that a bank is classified as a non-problem bank. Logit models adopt the following approach (Aldrich and Nelson, 1984, p.48, Mandala, 1994, pp.23-6):

\[ \ln \frac{P_i}{1-P_i} = Z_i \]

With algebraic manipulation, we can solve for \( P_i \) using the following equation:

\[ P_i = \frac{e^Z}{(1 + e^Z)} \]

Assuming we adopt the probability of \( P_i \) for \( Y=1 \) given \( X_i \), then the probability of \( P = \{ (Y = 0) \text{ given } X_i \} = 1 - P_i \). The probability of \( N \) values of sample \( Y \) given all \( N \) sets of values \( X_i \) is calculated by multiplying the \( N \) probabilities:

\[ P(Y / X) = \prod_{i=1}^{n} P_i(1 - P_i) \]
ML estimation chooses the estimates of the intercept and the coefficients of parameters from a set of "k" independent variables (\( \hat{b} \)) which would make the ML estimation produce estimates for \( Y \) as large as possible. The likelihood function is:

\[
L(Y / X, b) = P(Y / X)
\]

Each trial value \( b \) provides a value of \( L(Y / X, b) \). ML estimation takes the value of \( \hat{b} \) which yields the largest value of \( L(Y / X, b) \) or \( \max_b L(Y / X, b) \).

Finally, we can derive the intercept and coefficients of the \( b' \)s by differentiating the probability equation with respect to \( a \) and \( b \), setting the results to zero and solving for the intended coefficients.

Recall the following equation:

\[
P(Y / X) = \prod_{i=1}^{n} P_i(1 - P_i)
\]

The likelihood function is:

\[
LP(Y / X) = \prod_{i=1}^{n} P_i(1 - P_i)
\]

To simplify the calculation, we transform the equation into logarithmic form and obtain the following equation:

\[
\log L = \sum_{i=1}^{n} [\log P_i + \log(1 - P_i)]
\]

\[
\frac{\partial (\log L)}{\partial \beta_1} = \sum_{i=1}^{n} \left[ \frac{\partial P_i}{\partial \beta_1} \right] P_i - \frac{\partial P_i}{\partial \beta_1} \frac{1 - P_i}{1 - P_i}
\]

\[
\frac{\partial (\log L)}{\partial \beta_k} = \sum_{i=1}^{n} \left[ \frac{\partial P_i}{\partial \beta_k} \right] P_i - \frac{\partial P_i}{\partial \beta_k} \frac{1 - P_i}{1 - P_i}
\]
Finally, we can solve for $\beta_1$ and $\beta_k$ using the TSP software package to get efficient estimators.

This study will employ cross-sectional and quarterly time-series data of financial ratios of banks from March 1989 to June 1995. In this estimation, there may be a problem with behaviour over time for a given cross-sectional unit and among the cross-sectional units themselves to get efficient parameters in the estimation (Judge et al, 1985, pp.515-60). According to Judge, we can classify the variation in behaviour over time and within cross-section units into five alternatives, as given in the following outline.

The equation of a linear model can be expressed in the following form:

$$y_{it} = \beta_{it} + \sum_{k=2}^{K} \beta_{kit} x_{kit} + e_{it} \quad (3.2)$$

The first alternative assumes that all constants and slope coefficients are the same for cross-sectional units and over time ($\beta_{it} = \beta_1$ and $\beta_{kit} = \beta_k$). Then, we can transform this model into the following equation:

$$y_{it} = \beta_1 + \sum_{k=2}^{K} \beta_k x_{kit} + e_{it} \quad (3.3)$$

This treatment also assumes that the different behaviour over cross-sectional units and time variations will be captured in the disturbance term ($e_{it}$). Therefore, $e_{it}$ will be heteroscedastic and autocorrelated.

The second alternative assumes that the constant varies between cross-sectional units only (i.e. the same over time) and the slopes are the same both for cross-sectional units and over time ($\beta_{it} = \beta_1 = \bar{\beta}_1 + \mu_{i1}$ and $\beta_{kit} = \beta_k$). We can express this model in the following equation:
\[ y_{it} = \bar{\beta} + \mu_i + \sum_{k=2}^{K} \beta_k x_{kit} + e_{it} \]  

where,
\( \bar{\beta} \) = the mean of \( \beta \) and  
\( \mu_i \) = the difference of \( \beta_i \) (\( i^{th} \) individual) from \( \bar{\beta} \)

The third alternative assumes that the constant varies between cross-sectional units and through time but the slope coefficients are the same (\( \beta_{it} = \bar{\beta} + \mu_i + \lambda_t \) and \( \beta_{sit} = \beta_k \)). The equation for this model is as follows:

\[ y_{it} = \bar{\beta} + \mu_1 + \lambda_t + \sum_{k=2}^{K} \beta_k x_{kit} + e_{it} \]  

where,
\( \lambda_t \) = the time series effects on all individuals

The fourth alternative assumes that the slope coefficients and constants vary between individuals (\( \beta_{it} = \beta_{it} = \bar{\beta} + \mu_i \) and \( \beta_{sit} = \beta_{si} = \bar{\beta} + \mu_i \)). Therefore, we can express this model in the following equation:

\[ y_{it} = \bar{\beta} + \mu_1 + \sum_{k=2}^{K} (\bar{\beta}_k + \mu_k) x_{kit} + e_{it} \]  

where,
\( \bar{\beta}_k \) = the mean of \( \beta \) and  
\( \mu_k \) = the individual specific component which is the difference of individual \( i \) from \( \bar{\beta}_k \)

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The fifth alternative assumes that the slope coefficients and constants vary between individuals and over time ($\beta_{it} = \bar{\beta} + \mu_i + \lambda_t$ and $\beta_{kt} = \bar{\beta}_k + \mu_{kt} + \lambda_{kt}$). In mathematical terms, this model is as follows:

$$y_{it} = \bar{\beta} + \mu_i + \lambda_t + \sum_{k=2}^{k} (\bar{\beta}_k + \mu_k + \lambda_k) x_{kit} + e_{it}$$ (3.7)

However, it is still unclear whether the effects on the coefficients of variables of each cross-sectional unit ($\mu$) and over time ($\lambda$) are fixed or random. If these effects are assumed as fixed, we can use dummy variable models for the constant and the seemingly unrelated regression models for the slope coefficients. Alternatively, if the effects are assumed to be random, we can use Error Component Models for the intercept (Mundlak, 1978a) and Swamy Random Coefficient Models for the slope coefficients (Swamy, 1970). Another approach is recognised within the Hsio Random Coefficient Models, which assume that effects on the intercept and slope coefficients are random (Hsio, 1974, 1975).

The choice of fixed or random effects for the model depends on whether the $\mu_i$ and $X_i$ are correlated. The random assumption results in a more efficient estimator when correlation between $\mu_i$ and $X_i$ exists by assuming a certain distribution of the $\mu_i$. However, Judge (1985, p.527) suggests that the random assumption may produce inefficient estimators when the true distribution of $\mu_i$ is different from the assumption. Therefore, dummy variable estimators may be better since we are not sure of the distribution of $\mu_i$.

This study will employ two models. Model 1 assumes that the intercept and slope coefficients are the same between individuals and over time. Model 2 assumes that the intercept and slope coefficients vary between groups using a fixed effects model, but that they are the same between individuals within groups and over time. In other words, the coefficients of parameters in model 1 are assumed to be valid for all groups and the
coefficients of parameters in model 2 are different for each group. The aim of model 2 is to test whether each group of banks has different significant coefficients of parameters. The results of model 2 may show different significant parameters for each group compared to that in Model 1. This information is useful for regulatory authorities as it enables them to focus on the particular risks to which the groups are sensitive in supervising banks.

In mathematical terms, model 1 can be expressed in the following equation:

\[ y_{it} = \beta_1 + \sum_{k=1}^{k} \beta_k x_{kit} + e_{it} \]  

(3.8)

where \( i \) = individual bank, \( t \) = time, \( k \) = the "\( k \)th" independent variable. The distribution of \( e_{it} \) is assumed to be normal \([ i. i. d. N(0, \sigma^2) ]\).

In mathematical terms, model 2 can be shown in the following equation:

\[ y_{git} = \beta_g + \sum_{k=1}^{k} \beta_{gk} x_{gkit} + e_{git} \]  

(3.9)

where,  
- \( g \) = groups of banks (\( g = 1........G \));  
- \( i \) = individual banks (\( i = 1........N \));  
- \( t \) = time series (\( t = 1........T \))  
- \( k \) = the "\( k \)" independent variables (\( k = 1........K \)).

The disturbance term, \( e_{git} \), is also assumed to be normally distributed \([ i. i. d. N(0, \sigma^2) ]\).

This study adopts dummy variables of fixed effect models for the intercept and seemingly unrelated regression of fixed effect models for the slopes. According to Baltagi (1995, p.179), Mandala (1994), and McFadden (1984), the cross-section treatment applies for panel data of limited dependent variables since we assume there is no random effect for individuals.
The treatment for the use of dummy variables for the intercepts is outlined in the following table:

### Table 3.1.
**Dummy Variables for Constants**

<table>
<thead>
<tr>
<th></th>
<th>D1</th>
<th>D2</th>
<th>D3</th>
<th>D4</th>
<th>D5</th>
</tr>
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<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

To illustrate the treatment of fixed effects for slope coefficients using a seemingly unrelated regression model, we employ the following equation:
Chapter 3 - An Empirical Study of the Determinants of Potential Problem Banks in Indonesia

\[
y_{git}^{*} = \beta g_{1} x_{g_{1}k_{1}i}^{*} + \beta g_{2} x_{g_{2}k_{2}i}^{*} + \ldots + \beta g_{n} x_{g_{n}k_{n}i}^{*} + \beta g_{1} k_{2} x_{g_{1}k_{2}i}^{*} + \ldots + \beta g_{2} k_{2} x_{g_{2}k_{2}i}^{*} + \ldots + \beta G k_{2} x_{G k_{2}i}^{*} + e_{git}^{*}
\]

\[
y_{git} = y_{g_{1}i} \rightarrow \text{if } g = 1 \text{ and } i = 1, \ldots, n_1
\]

\[
y_{g_{2}i} \rightarrow \text{if } g = 2 \text{ and } i = n_1 + 1, \ldots, n_2
\]

\[
y_{G_{i}i} \rightarrow \text{if } g = G \text{ and } i = n_{g-1} + 1, \ldots, n_g
\]

\[
x_{g_{1}k_{1}i}^{*} = \begin{cases} x_{g_{1}k_{1}i} & \text{if } g = 1 \text{ and } i = 1, \ldots, n_1 \\ 0 & \text{otherwise} \end{cases}
\]

\[
x_{g_{2}k_{1}i}^{*} = \begin{cases} x_{g_{2}k_{1}i} & \text{if } g = 2 \text{ and } i = n_1 + 1, \ldots, n_2 \\ 0 & \text{otherwise} \end{cases}
\]

\[
x_{G k_{1}i}^{*} = \begin{cases} x_{G k_{1}i} & \text{if } g = G \text{ and } i = n_{g-1} + 1, \ldots, n_g \\ 0 & \text{otherwise} \end{cases}
\]

\[
e_{git}^{*} = e_{i} \rightarrow \text{if } g = 1 \text{ and } i = 1, \ldots, n_1
\]

\[
e_{2i} \rightarrow \text{if } g = 2 \text{ and } n_1 + 1, \ldots, n_2
\]

\[
e_{G_{i}} \rightarrow \text{if } g = G \text{ and } i = n_{g-1} + 1, \ldots, n_g
\]

where,

\( g \) = the groups of banks \( (g = 1,2, \ldots, G) \)

\( k \) = the "k" independent variables \( (k = 1,2, \ldots, K) \)

\( i \) = the individual bank \( (i = 1,2, \ldots, N) \)

\( \beta \) = the coefficient of independent variables

\( x \) = the independent variable

\( y \) = the dependent variable

\( t \) = the time series \( (t = 1,2, \ldots, T) \)
\[ n_g = \text{the number of observations in group } g \text{ and } n_1 + n_2 + \ldots + n_g = N \]

If \( y \) belongs to \( g = 1 \), this model will give a zero value to independent variables and a constant for \( g \neq 1 \).

3.3. Data

This study employs quarterly data of banks' financial ratios from March 1989 to September 1995. Because the data was collected in 1996, the last observation is at the end of September 1995. The last observations (September 1995), which relate to 230 banks, are excluded from the model generation. This data is, instead, used for out of sample test purposes. An out of sample test is conducted in this study to examine the model's ability to estimate out of sample observations. The year of 1989 was the starting point of a new era for the banking industry in Indonesia. The central bank restructured banking regulation in October 1988 (hereafter, called simply "the reform"). The reform allowed for the establishment of new banks in Indonesia, including joint venture banks. Many other bank regulations were revised (see Chapter 1). Therefore, the banking industry after the reform was totally different from that before 1988. Because of this, this study employs quarterly data from March 1989.

The following outline is a general overview of the development and structure of the banking industry in Indonesia. The number of banks and their offices increased significantly after the reforms. In September 1995, there were 241 commercial banks, excluding rural banks which accounted for around 9072 banks (Bank Indonesia, 1995). Although the number of rural banks is very high, their share of banking business is very low. In November 1994, their share of total assets only amounted to 0.61% (Bank Indonesia, 1995). The rural banks will thus be excluded from this study as their contribution to the industry is insignificant. Commercial banks consist of: 7 state banks; 71 private foreign exchange banks (PFEB); 95 private non-foreign exchange banks (PNFEB); 31 joint venture banks (JVB); 10 foreign banks (FB); and 27 regional development banks (RDB). The differences between each group of banks depend on ownership and authorisation in foreign exchange operations.
Based on their ownership, banks may be distinguished as state banks, private banks, foreign banks, joint venture banks and regional development banks. Based on authorisation, banks may be categorised as foreign exchange banks and non-foreign exchange banks. The study excludes 10 foreign exchange bank branches in Indonesia from this study because the risk of these banks cannot be assessed separately from their parents. Consolidated positions are required to assess these banks.

3.4. Dependent variables

Logit models have been widely used in social science to determine the probability that a particular event occurs (see Chapter 2) by using a range of independent variables. Some researchers use logit models to estimate the probability of bank failure. However, certain problems can cause inaccurate estimates. These problems include small sample size (related to bank failure) and lack of reliable published information. Additionally, the results would be biased if there were a substantial number of bank failures as a result of fraud. The argument is that the balance sheets and income statements cannot reflect the integrity of staff.

Prediction of the probability of bank failure is not appropriate for this study because only a few banks failed in Indonesia from 1970 to 1996 as a result of a “too big to fail” policy. However, there were some banks which were recognised as being in trouble. To determine which banks might prove problematic, this study adopts criteria which have been used by the Bank of Indonesia itself.

This study thus employs information on “problem” and “non-problem” banks as dependent variables. A bank can be defined as a “problem” if it satisfies one or both of the following criteria: first, the bank needs financial and/or management support from government to continue its operations; and second, its composite rating is either “poor” or “unsound” (Bank Indonesia, CL 23/21/BPPP, 28 February 1991). The composite ratings are calculated

*The rating is defined based on the following credit points: 81-100 is “sound”; 66-80 is “fairly sound”; 51-65 is “poor”; 0-50 is “unsound”.*
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monthly, based on financial reports and the judgment of supervisors. The central bank maintains a list of problem banks and updates it regularly. To insert the data into models, this study assigns symbols to dependent variables of “1” for problem banks and “0” for non-problem banks. By employing problem and non-problem banks as dependent variables, the supervisory authorities have more lead time to introduce corrective action for banks estimated as problems than for banks estimated as failures. If a bank has been categorised as a failure, the condition of the bank must be very serious and the authorities will have only limited time to provide appropriate remedial treatment. However, the consistency of parameters used to determine problem banks over time contributes significantly to the goodness of fit of the estimates in this study.

3.5. Independent variables

Independent variables consist of 14 financial ratios. These independent variables represent proxies for determinants of bank risks and, as discussed in Chapter 1, the probabilities of banks suffering losses are measured by their risks.

In general, bank risk consists of credit risk, interest rate risk, foreign exchange risk, liquidity risk, solvency risk and efficiency risk (see chapter 1 for details). There are other risks which are not covered in this study such as settlement risk, legal risk, fraud risk and exposure risk. The main reason is that there is little data to support analysis of these risks. The rationale for the relationship between risks and independent variables is discussed in the following section.

Sometimes, it is difficult to say precisely what the relationship is (i.e. sign) between dependent and independent variables. For example, a short position of call money (negative gap in maturity) creates a benefit for banks when interest rates drop and causes a loss when interest rates increase. This study will suggest the signs of independent variables under certain circumstances. The differences between the results and the suggestions will be
discussed in the analysis of results. The following sub-sections discuss the financial ratios which are used as independent variables in this study.

3.5.1. Ratio relating to credit risk

Credit risk is defined as the probability (i.e. risk) of default by borrowers. Bank Indonesia assesses asset quality to form a proxy for losses arising from default by borrowers by using the following procedure (Bank Indonesia, CL 23/12/BPPP, February 1991). First, bank supervisors classify the accounts of the borrowers into one of four categories -“good”, “substandard”, “doubtful” and “bad-debts” (loss)- by employing an agreed rule between the banking industry and the central bank. Second, bank supervisors calculate a proxy for the losses on each loan category based on an agreed rule. Third, bank supervisors estimate asset quality by summing the amount of proxied losses for all borrowers, and the result is then divided by total loans. Asset quality (AQ) represents credit risk in this regression. Theory suggests that the higher the AQ, the higher the probability of banks suffering problems.

3.5.2. Ratios relating to liquidity risk

Liquidity risk is the probability or risk of a bank being unable to meet its short-term obligations, such as current account and time deposit withdrawals and short-term money market liabilities, as they fall due. This study includes only the “banking book” items because only a few banks operate trading books (i.e. derivatives). The following financial ratios serve as proxies for liquidity risks:

a. Call money to total assets ratio (CMAR)

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5 The rule relies on variables such as the delay in repayment, including interest and instalments, expiration, and lack of security taken as collateral.

6 A proxy for losses is calculated according to the following rules: a good loan is defined as zero loss; substandard is defined as a 50% loss; doubtful is defined as a 75% loss, and bad-debt is defined as a 100% loss.
Call money is funds borrowed from the money markets with a maximum term of 90 days. Banks normally use these sources of funds to satisfy a minimum liquidity requirement imposed by the central bank at the end of the day after the clearing house has closed. The hypothesis is that the higher a bank’s funding on this basis, the higher the probability of its suffering problems (+ sign). This ratio also reflects the sensitivity of banks to interest rate risk as a result of the volatility of interest rates in money markets.

b. Discount window borrowing to total assets ratio (DAR)

The discount window is a facility for banks which suffer illiquidity to borrow a certain amount of money from the central bank at market interest rates using money market certificates as collateral. Normally, banks use this facility when they are unable to borrow money from the markets or other banks. In this case, the central bank acts as the lender of the last resort. However, the use of this facility is subject to tight requirements. Theory suggests that the higher this ratio, the higher the probability that a bank is suffering from liquidity problems (+ sign).

c. Loans to deposits ratio (LDR)

The loans to deposits ratio assesses the role of deposits in financing loans. A higher ratio means a lower proportion of loans is financed by deposits. Other funds are available to finance loans such as call money, discount window borrowing and other market borrowings (this study assumes that there is no paid-up capital to finance loans). The interest rates on these other funds, however, are higher than for deposits and, especially for call money, the interest rates are volatile. Theory suggests that the higher this ratio, the higher the probability of a bank suffering liquidity problems (+ sign).

3.5.3. Ratios relating to solvency risk

The solvency ratio represents the ability of banks to meet losses without being liquidated. This ratio normally measures net worth compared with total assets or borrowed funds. However, this study adopts the capital to total assets ratio (CAR) to proxy solvency risk.
The components of capital in this ratio consist of paid up capital, including capital stock, general reserves, retained earnings, and unpublished retained earnings. This study includes a delta earning of each quarter in the components of capital. The capital at problem banks must be higher than that of non-problem banks as a result of the adoption of a risk-based capital adequacy (Basle Accord of 1988) assessment regime since 1988. The rationale is that the problem banks have to maintain higher capital as reserves for settling the recognised losses. Thus, the higher this ratio, the lower the probability of a bank suffering solvency problems7 (- sign).

3.5.4. Ratios relating to interest rate risk

Interest rate risk is the risk or probability of a bank suffering losses because of the volatility of interest rates (the detail of this discussion is presented in Chapter 1). Banks with long funding positions (i.e. positive maturity gaps) will benefit when interest rates decrease and the banks will lose money when interest rates increase. Banks with short positions (i.e. negative maturity gaps) will lose money when interest rates decrease and benefit when interest rates increase.

To detect the sensitivity of banks to interest rates, this study uses three independent variables: CMAR, LDR and IRR (interest rate risk). CMAR and LDR have been discussed in the liquidity risk section. Additionally, this model also uses IRR as an independent variable to detect the sensitivity of banks in general to interest rate movements. The interest rate data used in this model are daily money market rates -Jakarta inter-bank offered rates (JIBOR)- and these are transformed into interest rates on a quarterly basis using delta weighted averages. To proxy for the interest rate risk, we multiply this delta interest rate by net call money positions. Finally, IRR is derived from the following equation:

\[ IRR = (R_t - R_{t-1})CMP \] (3.12)

7 The information on risk adjusted capital ratios (BIS approach) cannot be used in this study for secrecy reasons.
where,

\[ R_t \quad = \text{the real interest rate in a given quarter} \]
\[ R_{t-1} \quad = \text{the real interest rate in the previous quarter} \]
\[ CMP \quad = \text{the net call money positions} \]

We expect a positive sign for IRR as theory suggests that many banks suffer problems because of the volatility in interest rates.

3.5.5. Ratios relating to efficiency risk

The ROA and ROE ratios are the main ratios used to measure efficiency risk. The numerators of these ratios (i.e. returns) are derived from the retained earnings figures of income statements. However, these ratios are unable to show which components of profit and loss contribute significantly to the ratio. For this reason, this study examines efficiency risk using components or items in the profit and loss statements such as income, costs and expenses. Additionally, this section also examines the efficiency of funds allocated for fixed assets using a fixed assets capital ratio.

a. **Return on Assets (ROA) ratio**

The ROA ratio measures the ability of banks to generate incomes from each unit of asset. Theory suggests that the higher the ROA, the lower the probability of banks suffering problems (- sign).

b. **Return on Equities (ROE) ratio**

The ROE ratio measures the ability of banks to generate incomes from each unit of equity. Theory also suggests that the higher the ROE, the lower the probability of banks suffering problems (- sign).

c. **Operating income ratio (OIR)**

The OIR is the ratio of non-interest operating incomes to total income. The OIR consists of incomes from trading activities and incomes from other services including fees. This ratio measures the ability of banks to generate incomes from non-loans or
investments. A lower ratio indicates that a bank has problems earning revenues from non-loans and investment activities. This condition implies that banks' operations are not efficient. Therefore, theory suggests that the lower this ratio, the higher the probability of a bank suffering problems (- sign).

d. **Interest income ratio (IIR)**

The IIR is the ratio of interest income to total incomes. This ratio measures the ability of banks to generate interest revenues from their investments. The objective of including this variable in the regression is to examine whether interest incomes contribute significantly to the problems faced by banks. Since the banks concentrate on investment activities, theory suggests that the higher this ratio, the lower the probability of a bank suffering problems (- sign). However, this causation is not appropriate for banks which generate income mainly from foreign exchange trading, which will lower the resultant IIR.

e. **Interest cost ratio (ICR)**

The ICR is the ratio of interest costs to total costs. The objective of employing this ratio is to examine whether banks can manage interest costs effectively. A higher ratio implies that banks have incurred higher interest costs (i.e. inefficient). A measure of the ability of banks to control interest costs is the interest rate margin. However, because of limited information, this study will not employ interest rate margins in the regressions. Theory suggests that the higher the ICR, the higher the probability of a bank suffering problems (+ sign).

f. **Fixed assets capital ratio (FACR)**

The FACR is the ratio of fixed assets to capital. The FACR measures the effectiveness of banks' operations in allocating funds to investments which generate incomes. Because fixed assets are not earning assets, a high ratio is an indication of inefficiency in a bank's operations. Theory thus suggests that the higher this ratio, the higher the probability of a bank suffering problems (+ sign).
g. **Loan provisions ratio (LPR)**

LPR is the ratio of loan provisions to total loans. The objective of employing this ratio is to examine the ability of banks to build reserves for both expected and unexpected losses. A high ratio shows that banks have enough funds to cover loan losses. Theory suggests that the higher this ratio, the lower the probability of a bank suffering problems because the bank will have enough funds to back up its losses (- sign).

### 3.5.6. Exchange rate risk

To detect the sensitivity of banks to the volatility of exchange rates, this study employs the exchange rate of the US dollar against the domestic currency, the Indonesian Rupiah (IDR). This variable is represented by FXDER. The US$ dominates the positions of Indonesian banks because most foreign exchange transactions are denominated in the US dollar. Additionally, reports of foreign exchange positions made to Bank Indonesia are denominated in US$. Therefore, this study only employs data for the US$/IDR exchange rate. To calculate the FXDER, this study adopts continuous compounds (i.e., log returns) of the quarterly average of exchange rate returns and multiplies the results by the foreign exchange positions. In mathematical terms, the FXDER can be expressed by the following equation:

\[
FXDER = \ln \left( \frac{E_t}{E_{t-1}} \right) FX
\]

(3.13)

Theory suggests that the higher the foreign exchange volatility, the higher the probability of a bank suffering problems. This study assumes that the exchange rate US$/IDR is highly volatile and we therefore expect a positive sign for this variable.

### 3.6. Empirical results

---

8 This condition may reflect the fact that the IDR was pegged to the USD.
The discussion in this section begins with the signs of parameters and continues with testings of the coefficients. We discuss only the signs which are different from a priori expectation and attempt to explain why they occur. The discussion begins with the analysis of results in model 1 and is followed by discussion of the results in model 2.

Model 1 produces 3 signs (i.e. + for IIR, CAR and - for LDR) which differ from expectations (see Table 3.2). Logically, one expects a negative sign for IIR whereas the result shows a positive sign. There are many possible explanations for this situation. The best possible explanation is that most of the problem banks try to make more money by charging higher interest rates on lending but they have to pay higher interest rates on borrowed funds. Therefore the IIR must be relatively high but the interest rate margin is relatively low. This policy is common for problem banks where operational costs and expenses are relatively high. Alternative explanations are also possible, such as incurring losses on foreign exchange trading and fraud.

The sign for CAR also differs from expectations. This condition shows that most problem banks post high CARs to comply with risk-adjusted capital regulation. Another variable which gives a different sign from that expected is LDR. While a positive sign for LDR is expected, the model produces a negative sign. The negative sign means that the higher the LDR, the lower the probability of banks suffering problems. The higher LDR (LDR>1) means that banks finance loans from other sources of funds instead of using deposits. Other sources of funds may consist of borrowed funds from the money market or other banks. The negative sign shows that the banks which used borrowed funds gained a reduced probability of suffering problems. However, the coefficients of IIR and LDR are not significant using a t-critical value of 1.96 (a confidence interval of 95%). To examine whether the signs of those coefficients remain consistent across the groups, we will discuss the results of model 2 later in this section.

Based on the t-distribution table, the results show that six variables (CMAR, FXDER, ICR, IRR, IIR, LDR) are insignificant even with a 0.10 confidence level. These variables represent interest rate risk (IRR, LDR and CMAR), foreign exchange risk (FXDER) and
efficiency risk (IIR, ICR). To test whether these coefficients are still zero when they interact simultaneously, we use the log likelihood ratio test by excluding the insignificant variables from the model. The results show that the log likelihood ratio is 3.99 ($L_0 = -2012.69$ and $L_1 = -2104.68$). Based on the chi-square distribution table with a degree of freedom (df) of 6, we accept the hypothesis that the coefficients of the omitted variables are zero at the 5% confidence level. Finally, we can conclude that only eight variables (i.e. AQ, CAR, FACR, DAR, LPR, OIR, ROA, and ROE) are significant. Based on the results in model 1, we can thus derive the conclusion that banks, individually, in Indonesia are not very sensitive to foreign exchange risk or interest rate risk, but that they are sensitive to credit risk, efficiency risk, solvency risk and liquidity risk.

To compare the results in model 1 and model 2, this study employs the pseudo-\( R^2 \) proposed by McFadden (1973, p.121). The \( R^2 \) is derived from the following calculation (see Appendix 2.1 for detail):

\[
R^2 = 1 - \frac{-2,012.69}{-3,253.75} = 0.38
\]

where, 
\( l_m = -2,012.69 \) and \( l_o = -3,253.75 \)

This \( R^2 \) is lower than the \( R^2 \) in model 2 considered later in this discussion.

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9 Log likelihood ratio test = \(-2(2103.36-2104.1)\) = 1.48.
### Table 3.2
Regression Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>Intercept</th>
<th>AQ</th>
<th>CAR</th>
<th>CMAR</th>
<th>DAR</th>
<th>FACR</th>
<th>FXDER</th>
<th>ICR</th>
<th>IIR</th>
<th>LDR</th>
<th>LPR</th>
<th>OIR</th>
<th>ROA</th>
<th>ROE</th>
<th>Log-likelihood</th>
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<tr>
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<td>-5.61</td>
<td>-2.15</td>
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<td>-3.47</td>
</tr>
<tr>
<td>Prob</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.65</td>
<td>0.01</td>
<td>0.01</td>
<td>0.26</td>
<td>0.22</td>
<td>0.89</td>
<td>0.68</td>
<td>0.55</td>
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<td>0.28</td>
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<td>0.003</td>
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<tr>
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<td>27.51</td>
<td>9.28</td>
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<td>2.85</td>
<td>2.78</td>
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<tr>
<td>Prob</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>-</td>
<td>0.00</td>
<td>0.01</td>
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<tr>
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<td><strong>Group 1</strong></td>
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<td>1.47</td>
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<td>0.006</td>
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<td>-6.55</td>
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<tr>
<td>t-statistic</td>
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<td>3.51</td>
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<td>0.91</td>
<td>-1.86</td>
<td>-2.84</td>
<td>0.44</td>
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<tr>
<td>Prob</td>
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<td>0.00</td>
<td>0.00</td>
<td>0.48</td>
<td>0.25</td>
<td>0.12</td>
<td>0.43</td>
<td>0.00</td>
<td>0.57</td>
<td>0.36</td>
<td>0.06</td>
<td>0.00</td>
<td>0.66</td>
<td>0.00</td>
<td>0.76</td>
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<tr>
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<tr>
<td>Coefficients</td>
<td>0.95</td>
<td>0.25</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.02</td>
<td>0.15</td>
<td>-0.05</td>
<td>-4.98</td>
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<td>8.76</td>
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<td>1.44</td>
<td>-0.37</td>
<td>0.33</td>
<td>-0.42</td>
<td>-0.40</td>
<td>1.35</td>
<td>-2.29</td>
<td>-10.78</td>
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<tr>
<td>Prob</td>
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<td>0.38</td>
<td>0.68</td>
<td>0.62</td>
<td>0.15</td>
<td>0.71</td>
<td>0.65</td>
<td>0.74</td>
<td>0.67</td>
<td>0.69</td>
<td>0.18</td>
<td>0.02</td>
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</tr>
<tr>
<td>Coefficients</td>
<td>-0.10</td>
<td>0.24</td>
<td>0.01</td>
<td>-0.01</td>
<td>0.28</td>
<td>0.00</td>
<td>-</td>
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<td>-0.04</td>
<td>0.01</td>
<td>-1.43</td>
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<td>17.00</td>
<td>7.01</td>
<td>-1.41</td>
<td>4.18</td>
<td>0.36</td>
<td>1.47</td>
<td>-2.44</td>
<td>-0.79</td>
<td>-1.88</td>
<td>-1.26</td>
<td>0.85</td>
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<tr>
<td>Prob</td>
<td>0.71</td>
<td>0.00</td>
<td>0.00</td>
<td>0.16</td>
<td>0.00</td>
<td>0.72</td>
<td>-</td>
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<td>0.43</td>
<td>0.06</td>
<td>0.21</td>
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<tr>
<td>Coefficients</td>
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<td>0.13</td>
<td>0.00</td>
<td>-0.08</td>
<td>0.05</td>
<td>0.00</td>
<td>0.03</td>
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<td>-0.01</td>
<td>0.01</td>
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<td>3.82</td>
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<td>-0.21</td>
<td>1.39</td>
<td>-0.86</td>
<td>2.04</td>
<td>-0.01</td>
<td>-0.73</td>
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<td>-0.06</td>
<td>0.22</td>
<td>3.10</td>
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</tr>
<tr>
<td>Prob</td>
<td>0.92</td>
<td>0.00</td>
<td>0.76</td>
<td>0.82</td>
<td>0.83</td>
<td>0.16</td>
<td>0.39</td>
<td>0.04</td>
<td>0.99</td>
<td>0.47</td>
<td>0.71</td>
<td>0.95</td>
<td>0.83</td>
<td>0.00</td>
<td>0.02</td>
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<td><strong>Group 5</strong></td>
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</tr>
<tr>
<td>Coefficients</td>
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<td>-0.01</td>
<td>0.02</td>
<td>-0.04</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.91</td>
<td>-0.03</td>
<td>-0.07</td>
<td>0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td>t-statistic</td>
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<td>11.65</td>
<td>-0.62</td>
<td>0.99</td>
<td>-0.49</td>
<td>0.98</td>
<td>0.20</td>
<td>0.36</td>
<td>0.87</td>
<td>-1.65</td>
<td>1.78</td>
<td>-0.37</td>
<td>1.47</td>
<td>-0.15</td>
<td>-0.67</td>
</tr>
<tr>
<td>Prob</td>
<td>0.00</td>
<td>0.00</td>
<td>0.54</td>
<td>0.32</td>
<td>0.63</td>
<td>0.33</td>
<td>0.84</td>
<td>0.72</td>
<td>0.39</td>
<td>0.10</td>
<td>0.08</td>
<td>0.71</td>
<td>0.14</td>
<td>0.88</td>
<td>0.50</td>
</tr>
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</table>
The results of model 1 are based on the assumption that the constant and slope coefficients are the same between individuals and over time. There is an argument that the results may be different if we employ more restrictive models such as model 2. Therefore, this study also employs model 2, which assumes that the constant and slopes vary among groups but are the same between individuals and over time, in order to examine whether each group of banks faces different risks as represented by the financial ratios. The following table shows the groups of banks in Indonesia:

<table>
<thead>
<tr>
<th>Banks</th>
<th>Group</th>
<th>Number of individuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>State Banks</td>
<td>I</td>
<td>7</td>
</tr>
<tr>
<td>Private Foreign Exchange Banks</td>
<td>II</td>
<td>71</td>
</tr>
<tr>
<td>Private Non-foreign Exchange Banks</td>
<td>III</td>
<td>95</td>
</tr>
<tr>
<td>Joint Venture Banks</td>
<td>IV</td>
<td>31</td>
</tr>
<tr>
<td>Regional Development Banks</td>
<td>V</td>
<td>27</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>231</td>
</tr>
</tbody>
</table>

The results of model 2 show that the intercept and constant coefficients for each group differ from that in model 1 (see Table 3.2). This shows that group effects are significant in this model. Based on a confidence level of 0.05, most of the groups are sensitive to credit risk (AQ), but none is sensitive to foreign exchange risk (FXDER). All groups are also sensitive to efficiency risk but only group 3 is sensitive to solvency risk (CAR).
The results for group 1 show that banks are sensitive to AQ, ICR, LPR, ROA at a 5% confidence level and to LDR at a 6% confidence level. Therefore, banks belonging to group 1 are very sensitive to credit risk (AQ), efficiency risk (ICR, LPR, ROA), and interest rate risk (LDR).

The results for group 2 show that banks are sensitive to AQ, OIR, ROA at a 5% confidence level. Therefore, banks belonging to this group are very sensitive to credit risk (AQ) and efficiency risk (OIR and ROA).

The results for group 3 show that the signs of AQ, CAR, DAR, IIR, and ROA are significant at a 5% confidence level and LDR is very significant at a 6% confidence level. In other words, banks belonging to this group are sensitive to credit risk (AQ), solvency risk (CAR), liquidity risk (DAR and LDR), efficiency risk (ROA), and interest rate risk (LDR).

The results for group 4 show that the signs of AQ, ICR, ROA and ROE are significant at a 5% confidence level. These findings imply that banks belonging to this group are very sensitive to credit risk (AQ) and efficiency risk (ICR, ROA and ROE).

The results for group 5 show that only AQ is significant at a 5% confidence level while IRR is significant at a 10% confidence level, and LDR is significant at a 8% confidence level. Therefore, banks belonging to this group are sensitive to credit risk (AQ), interest rate risk (IRR), and liquidity risk (LDR).

To measure the goodness-of-fit, we employ the same method as that in model 1. The $R^2$ is derived from the following (see Appendix 2.1 for details):

$$R^2 = 1 - \frac{-1,700.74}{-3,142.04} = 0.46$$

where,
Based on these results, model 2 is more efficient than model 1 in estimating the probability of banks being problems.

This study employs an out of sample test using the last observations (September 1995) which consist of 230 data points. The aim of this test is to examine the ability of the models to estimate the probability of banks being problems using data which are not employed to generate the models. The results of out of sample tests are shown in Table 3.4. The error classification in this study adopts cut-off points of 0.5 and 0.6. In general, model 2 produces fewer errors than model 1. Then, we conclude that model 2 is better than model 1.

Model 1 classifies 28 observations of non-problem banks as problem (i.e. error I type), or 12.17% of total observations (230), using a cut-off-point of 0.5. Error I type occurs if the model produces $P > 0.5$ for $Y = 0$ (see Appendix 2.1). Model 1 classifies 16 observations of problem banks as non-problem (i.e. error II type), or 6.96%. Error II type occurs if the model produces $P < 0.5$ for $Y = 1$. The total errors of estimates in model 1 is 19.13%, or 44 observations out of 230 observations, so that correct estimates account for 80.87%, or 196 observations. However, when we use a cut-off-point of 0.6, the total errors decrease to 16.96% and the correct estimates increase to 83.04%.

Model 2 produces more correct estimates than model 1. Using a 0.5 cut-off-point, model 2 predicts total errors of 13.91% and estimates 86.09% of observations correctly. The total errors decrease to 12.18% when we use a cut-off-point of 0.6, which we believe is the fair cut-off point because this study employs 1984 observations of problem banks (or 41.32%) and 2,817 observations of non-problem banks (or 58.68%). The errors mostly occur in the transition period from banks being classified as problem to non-problem or the other way round. Finally, we can conclude that model 2 produces better coefficients of estimates than those in model 1.
### Table 3.4
Error Summary

<table>
<thead>
<tr>
<th>Correct and error estimates</th>
<th>Cut off point of 0.5*</th>
<th>Cut off point of 0.6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>%</td>
</tr>
<tr>
<td>Correct estimates</td>
<td>obs</td>
<td>%</td>
</tr>
<tr>
<td>Error I type</td>
<td>28</td>
<td>12.17</td>
</tr>
<tr>
<td>Error II type</td>
<td>16</td>
<td>6.96</td>
</tr>
<tr>
<td>Total</td>
<td>230</td>
<td>100</td>
</tr>
</tbody>
</table>

*) The guidelines for choosing this cut off point are outlined in Table 2.3
3.7. Conclusions

3.7.1. Based on the coefficients of the regressions, model 1 produces significant coefficients for AQ, CAR, DAR, FACR, LPR, OIR, ROA, and ROE at a 5% confidence level. These parameters represent credit risk (i.e. AQ), solvency risk (i.e. CAR), liquidity risk (i.e. DAR) and efficiency risk (i.e. FACR, LPR, OIR, ROA and ROE). However, the coefficients of parameters which represent exchange rate risk (FXDER) and interest rate risk (i.e. CMAR, IRR and LDR) are insignificant at the 5% confidence level. Considering the findings in model 1, we can conclude that banks in Indonesia are not sensitive to exchange rate or interest rate risks, but they are sensitive to credit risk, liquidity risk, efficiency risk and solvency risk.

3.7.2. Each group in model 2 produces different and significant coefficients of parameters from those in model 1. This finding provides evidence that the group effects are significant. The coefficients of parameters which represent credit risk (AQ) for all groups are significant at a 5% confidence level. The parameter which represents solvency risk (CAR) is significant at a 5% confidence level only in group 3. The coefficient of the parameter which represents interest rate risk (IRR) is significant at a 10% confidence level in group 5; and LDR is significant at a 6% confidence level in group 1 and group 3, and at an 8% confidence level in group 5. Therefore, only group 3, group 1 and group 5 are sensitive to interest rate risk. The coefficients of parameters which represent foreign exchange risk (FXDER) are insignificant for all groups. Therefore, no group of banks in Indonesia is sensitive to foreign exchange risk. The coefficients of parameters which represent liquidity risk are identical with the parameters which represent interest rate risk. The additional parameter for liquidity risk is DAR which is significant only for group 3. Therefore, group 1, group 3 and group 5 are the only groups sensitive to liquidity risk. The coefficients of parameters which represent efficiency risk are mostly significant at a 5% confidence level, which is the case for group 1, group 2, group 3 and group 4. Only group 5 is not very sensitive to operational risk. Finally we can conclude that banks belonging to group 1 are sensitive to credit risk, interest rate risk, liquidity risk, and efficiency risk; banks belonging to group 2 are
sensitive to credit risk and efficiency risk; banks belonging to group 3 are sensitive to credit risk, solvency risk, interest rate risk, liquidity risk, efficiency risk; banks belonging to group 4 are sensitive to credit risk and efficiency risk; and banks belonging to group 5 are sensitive to credit risk, interest rate risk and liquidity risk. Based on the results in model 1, banks in Indonesia are not very sensitive to interest rate risk. However, the results in Model 2 suggest that group 3 and group 5 are very sensitive to interest rate risk. This information is obviously useful for bank supervisors as indicate which risk banks are likely to be sensitive to.

3.7.3. Based on the Pseudo-$R^2$, the results of the estimates in model 2 are more efficient than those in model 1. To test the accuracy of estimating the probability of problem banks, this study employ an out-of sample test which comprises 230 observations. Using a fair cut-off point (0.6), model 2 produces 12.18% of total errors and 87.82% of correct estimates while model 1 produces 13.91% of total errors and 86.09% of correct estimates. This shows that model 2 is more efficient than model 1.

3.7.4. To provide a fair comparison of the “performance” of these models with others, we have to consider the following criteria: (1) the proportion of problem and non-problem (e.g. failed and non-failed) banks in the sample; (2) the observations employed in the error classification (i.e. within sample or out-of sample); (3) the data employed to generate the model. This thesis can be characterised as follows: it employs 41.3% of problem banks and 58.67% of non-problem banks; it uses an out-of sample test for error classification; and it employs supervisory data to generate the models. Based on the literature survey, there is no other study which matches my models’ comprehensive characteristics. The best result on the error classification front in the determination of the probability of bank failure which employed a similar proportion of problem (46%) and non-problem banks was achieved by Sinkey (1975). Sinkey’s model estimates 82% of observations correctly while model 2 in this study estimates 87.82% correctly. Therefore, model 2 provides better estimates than Sinkey’s. Based on these results, this study suggests that model 2 can be used as an additional early warning system (tool) for bank supervisors in Bank Indonesia to help identify emergent problem banks.
3.7.5. In general, the insignificance of the ratio for foreign exchange risk (FXDER) may indicate that traditional operations still dominate within banks in Indonesia. However, this condition may not be valid for selected individual banks which engage actively in foreign exchange trading. This condition occurs because, within the sample, the number of problem banks which are authorised in foreign exchange transactions is smaller than the number of non-foreign exchange banks. However, many banks suffered problem because of foreign exchange trading. Bank Duta suffered illiquidity because of huge losses in foreign exchange trading in 1990 (see Chapter 1) and the Indonesian government rescued Bank Exim in 1997 due to foreign exchange losses. Many banks have failed since the IDR exchange rate has gradually dropped since 1997. These cases support the suggestion that there are some individual banks which are heavily exposed to foreign exchange rate risk.

3.7.6. There is no doubt that banks by group in Indonesia are sensitive to interest rate risk. Risk assessment modelling in the next chapter can be applied either in interest rate risk or exchange rate risk assessment. Models in this chapter find that banks by group in Indonesia are not very sensitive to foreign exchange rate risk. However, it is still unclear whether individual banks in Indonesia are sensitive to foreign exchange rate risk. To provide more information concerning the foreign exchange rate risk of individual banks, the next step in this thesis involves developing models for foreign exchange rate risk assessment using, as a sample, the commercial bank which represents the most active bank in foreign exchange trading in Indonesia.

3.7.7. It would be useful to analyse whether banks which required bail-out generate different results to problem banks. However, this was not be possible within this research because of a lack of data concerning which banks were bailed-out and which banks were not. Confidentiality, largely due to political reasons, currently precludes such analysis.
Chapter 4

Capital Adequacy Assessment with Respect to Market Risk

4.1. Introduction

There are many different definitions of capital. For the purposes of this thesis, I focus my attention on the definition of capital used in the theory of banking and finance. It is difficult to define capital since there are a range of different perceptions concerning its functions. Berger, Herring and Szego (1995) differentiate between capital market requirements and regulatory requirements. The market capital requirement is defined as the capital ratio that maximizes the value of banks. Regulators focus on the possible negative externalities that may result from bank default but these are not taken into account in market capital requirements. Modigliani and Miller (M&M, 1958) suggest that this regulatory capital requirement is different from that of the market requirement. They suggest that in a frictionless world of full information and perfect markets, a firm's capital structure cannot affect its value. On the other hand, the regulatory objective is to maintain the value of the bank in such a way that the probability of failure is low. Therefore, capital regulation is a matter of tradeoff between the marginal social benefit of reducing the risk of the negative externalities from bank failure and the marginal social cost of diminishing intermediation (Santomero and Watson, 1977).

Banks' capital can be defined as the sum of equity and debt that is not insured by any deposit insurance institution and which can absorb losses. In this case, capital functions as an internal insurance fund (Benston, 1994; Hempel, 1990; Wesson, 1985; and Llewellyn, 1989). However, Vojta (1973) suggests that management capabilities, the institution's liquidity, and maintaining access to markets also protect depositors and creditors from

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10 The M&M proposition is the term used to express the suggestion introduced by Modigliani and Miller that the regulatory capital requirement cannot influence the way the banks are managed. The market may thus play a significant role in affecting profit and loss.
bank insolvency. The adequacy of capital must be accompanied by proper management to ensure that the economic value of capital does not deteriorate.

Changes in the economic value of assets and liabilities automatically change the value of capital. When a bank shifts its assets to riskier assets and the nominal value of assets remains unchanged, the economic value of the deposits and borrowed funds goes down under the assumption that the bank has reduced its willingness to pay off its liabilities. The economic value of capital provides a better measure of the value of banks than historical value. However, there are many problems in calculating the economic value of capital due to uncertainties over the rate of return and the variance and covariance of the returns among activities.

This chapter discusses mainly the assessment methodologies of the economic value of capital, especially for banks. Regulatory authorities benefit from information related to economic value of capital for supervisory purposes. When the economic value of capital is below the minimum requirement, regulatory authorities will require bank management to add more capital. The main purpose of the minimum capital requirement is to prevent banks from failing. Therefore, a method is required to assess capital adequacy. This method must acknowledge and make provision for the factors that affect capital adequacy. These factors comprise several risks such as credit risk, market risk, operational risk, interest rate risk and legal risk. However, there are some factors which may create losses, but which are difficult to incorporate into the risk formulation, such as the quality of management, which is an important factor when determining efficiency, the competitive position of banks, and capital market capabilities. The focus of this thesis is the assessment of capital adequacy with respect to market risk.

This chapter is organised in the following way: Section 4.2 reviews the BIS's approach to capital adequacy assessment with respect to market risk; Section 4.3 discusses internal models for market risk; Section 4.4 discusses the pre-commitment approach; and Section 4.5 comprises the conclusions.
4.2. The BIS's approach to capital adequacy assessment with respect to market risk

The discussion below begins by reviewing the risk calculation approach which was introduced by the BIS in 1988. To calculate credit risk, the Committee on Banking Supervision, operating under the auspices of the BIS, (from now on this study will use the phrase “the Committee”) set out its approach in the Basle Capital Accord of 1988 (“the Accord”). One of the purposes of the Accord was to reduce the inequality of treatment via capital adequacy regulation to help provide the same competitive opportunities for international banks. This approach has been adopted by most countries in the world including Indonesia. However, this approach has attracted many criticisms. According to Hall (1994), the Accord contains many weaknesses. Golding (1994) suggests that the ratios stipulated in the Accord are unrelated to true risks.

The framework can be expressed in mathematical form as shown by the following equation (Hall, 1994):

\[
RAR(\%) = \frac{ACB}{TOWRA} = \left\lfloor \sum_{i=1}^{S} \sum_{j=1}^{U} \left( A_{ij} W_{ij} \right) + \left( \sum_{i=1}^{S} \sum_{j=1}^{U} \sum_{k=1}^{X} B_{ijk} X_{jk} W_{ij} \right) + \left( \sum_{i=1}^{S} \sum_{j=1}^{U} \sum_{k=1}^{X} C_{ijk} X_{jk} \left( W_{ij} + M \right) W_{ij} \right) \right\rfloor
\]

- \( RAR \) = risk-asset ratio
- \( ACB \) = adjusted capital base
- \( TOWRA \) = total of weighted risk assets
- \( A_{ij} \) = value of the \( i^{th} \) asset with risk weight \( W_{ij} \)
- \( B_{ijk} \) = notional principal amount of off-balance sheet activity \( i \) with risk weight \( W_{ij} \) and conversion factor \( X_{jk} \)
- \( C_{ijk} \) = notional principal amount of the interest-rate or exchange-rate-related activity \( i \) with risk weight \( W_{ij} \) and conversion factor \( X_{jk} \)
- \( S \) = number of distinct asset components
- \( U \) = number of distinct off-balance-sheet activities (excluding interest-rate- and exchange-rate-related activities)
- \( X \) = number of distinct interest-rate and exchange-rate-related off-balance-sheet instruments
\[ M = \text{mark-to-market value of underlying contract} \]

The Committee was aware of some of the deficiencies in the Accord's attempt to address practical and universal needs. The Committee also recognised that many risks apart from credit risk may occur in banks. Therefore, the Committee agreed from the beginning to eventually capture market risk.

In April 1993, the Committee introduced a capital adequacy proposal to accommodate market risk in addition to credit risk. The proposal was revised several times and the final revision was released in January 1996. This revision actually represents an attempt to accommodate the industry's requests and comments concerning the adoption of internal models. The discussion below contains the framework, risk components and risk valuation methodologies of the BIS proposal for capital regulation with respect to market risk.

4.2.1. Framework

The proposal contains methodologies on how to measure market risk, define capital and calculate minimum capital requirements for banks. The proposal adopts the following framework\(^{11}\): (1) separating the "trading" from the "banking" books; (2) breaking the market risk into interest rate risk, foreign exchange risk, equity risk and commodities risk, and the treatments of derivatives; (3) calculating foreign exchange risk arising from both the "trading" and "banking" books; (4) adopting the "building block" approach where each market risk is calculated as the sum of specific risk and general market risk; (5) aggregating the risk in each component in order to get the total risk; (6) suggesting a treatment for option derivatives.

According to the Committee, the trading book is defined as:

\(^{11}\) Information in this section is mainly derived from BIS' proposals with respect to market risk (April 1993 and January 1996). See also Hall, 1995 and 1996.
"the positions in financial instruments which are intentionally held for short-term resale and/or which are taken on by the bank with the intention of benefiting in the short-term from actual and/or expected differences between their buying and selling prices, or from other price or interest-rate variations, and positions in financial instruments arising from matched principal brokering and market making, or positions taken in order to hedge other elements of the trading book". (BIS 1996, p.1)

There are some circumstances where non-trading instruments or off-balance sheet positions which are used to hedge trading activities and trading positions are used to hedge the banking book. The proposal excludes these transactions from the market risk capital charge and subjects them, instead, to the credit risk charge as proposed in the original Accord. The framework for calculating minimum capital requirements using the standardised methodology is shown in figure 4.1.

Figure 4.1.
Framework for Calculating the BIS Minimum Capital Requirements

Note: 1. The derivative instruments are classified according to the underlying assets (interest rate, Forex, commodity or equity)
2. The standardised rules on capital charges in this case are just for market risk.
As mentioned in the previous section, the standardised methodology adopts the "building-block" approach in which specific risk and general market risk are calculated separately. As shown in Figure 4.1, market risk is the accumulation of market risks which occur in the banking book (i.e. foreign exchange risk and commodity risk) and the trading book (foreign exchange risk, interest rate risk, commodity risk and equity risk). Finally, we can identify that the overall minimum capital charge under the BIS’s standardised methodology comprises the following items: (1) The minimum capital charge calculated by using the original Accord of 1988 (this calculation excludes debt securities in the trading book and all positions in commodities; however it includes counterparty risk deriving from all over-the-counter derivatives, regardless of whether they are in the trading or the banking book). (2) The arithmetical summation of the minimum capital charges for market risk. Detail of technical guidelines are shown by appendices 4.4-4.8.

4.2.2. Some pitfalls in the BIS’s proposal

To examine whether the proposal contains deficiencies, this study will adopt the ideal capital adequacy standard suggested by Taylor (1993). According to Taylor, an ideal capital standard should satisfy the following criteria: (1) ensure that there is sufficient equity capital to cover most losses in order to reduce the probability of failure; (2) impose a minimum regulatory burden on banks and minimise the regulatory barriers to entry; (3) cover all the financial risks which banks may encounter; (4) consider portfolio effects (i.e. require more capital for concentrated risk); (5) treat risk consistently in relation to capital; (6) provide reward for accurate risk measurement (i.e. lower risk and good management deserve to have less capital); (7) it must be durable and flexible, in the sense of not requiring frequent update and flexible enough to accommodate financial developments. The discussion below adopts these criteria in order to evaluate the BIS proposal.

4.2.2.1. Amount of required capital

By introducing a minimum capital adequacy requirement with respect to market risk under the amendment to the Basle Accord, total required capital will increase. However, there
is no assurance that those banks which meet the minimum capital requirement will not encounter financial problems in the future. Failure may still occur for one or more of the following reasons: (1) the BIS proposal ignores the risk relationship among risk factors; (2) there are many possible risks which are not covered, such as operational risk and fraud risk.

4.2.2.2. Comprehensiveness

The proposal includes only market risk in the trading book. Levonian (1994) suggests that the proposal should also cover interest rate risk arising from the banking book, such as loans and deposits. Additionally, the uncertain distinction between the banking and trading book in certain circumstances may provide an incentive for banks to shift positions from the trading to the banking book or the other way round depending on what benefit the bank is looking for. This criticism was raised by the Institute of International Finance (IIF) which represented 177 banks in the US (Shirreff, 1994).

4.2.2.3. Regulatory constraints

Many banks have been implementing more accurate risk management models for internal purposes for some time. The proposal still requires banks to generate additional capital (a multiplication factor) to cover unanticipated shocks. This may result in banks running two models (standardised and internal models) for the same purpose (White, 1995). This condition limits banks' efficiency.

4.2.2.4. Portfolio effects

The BIS proposal calculates total portfolio risk by summing the individual risk factors. The proposal thus implicitly assumes that risk factors in the portfolio positions are perfectly positive correlated (+1). The following equation is the expression in mathematical form of
this assumption (Section 4.3.4.2 shows the detailed mathematical explanation of this theory):

\[
R_{AB} = \sqrt{A^2 \sigma_A^2 + B^2 \sigma_B^2 + 2 \rho_{AB} \sigma_A \sigma_B B}
\]  

(4.2)

where,

\( R_{AB} \) = the risk of investment in asset A and asset B

\( S_A \) = the risk of investment in asset A

\( S_B \) = the risk of investment in asset B

\( A \) = the current exposure of investment in asset A

\( B \) = the current exposure of investment in asset B

\( r_{AB} \) = the correlation of risk between investment in asset A and asset B

If \( r_{AB} = +1 \), then

\[
R_{AB} = \sqrt{A^2 \sigma_A^2 + B^2 \sigma_B^2 + 2(1) \sigma_A \sigma_B B}
\]

\[
= \sqrt{(A \sigma_A + B \sigma_B)^2}
\]

\[
= A \sigma_A + B \sigma_B
\]

In fact, the correlation among risk factors is not always +1. There may even be negative correlations.

**4.2.2.5. Equivalent treatment of risks**

The BIS proposal adopts universal capital charges for foreign exchange risk (8%), equity risk (8%) and commodity risk (15%). In fact, the volatility of one currency differs from another, and similarly for equities and commodities (Economic Bulletin, 1994, pp.63-8).

**4.2.2.6. Rewarding precision in risk management**
Some multinational banks normally adopt risk calculation models that contain an embedded solution to the deficiencies in the BIS proposal as discussed in point 4.2.2. In other words, these banks have implemented more prudent risk management models than ordinary banks which have not adopted any risk management models. However, these banks are treated similarly (i.e. no reward) to ordinary banks which, apparently, simply adopt the BIS proposal in their risk management. This treatment discourages banks from developing and adopting better and more accurate risk calculation models.

4.2.2.7. Durability

In general, the BIS proposal is unable to accommodate the risk valuations arising from derivative instruments, especially options (i.e. non-linear relationship between the price and risk factors). On the other hand, the development of derivative instruments in terms of the percentage of banks’ operations has increased rapidly. The BIS proposal fails to accurately measure risk for options. Finally, the approach adopted by the BIS would seem to be out of date and fails to accommodate the needs of advanced financial risk management. However, the proposal can be applied widely in other countries as a result of its simplicity and practicality. This reflects a belief that universal and practical considerations are the most important characteristics of international capital regulation, especially for traditional banks.

Based on some pitfalls above, the next section suggests models to assess market risk. The models will accommodate the criticisms addressed to regulatory standardised methodologies.

4.3. Models to assess market risk

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
Chapter 4 - Capital Adequacy Assessment with Respect to Market Risk

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 (for further details, see Figure 4.3).

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.

4.3.1. Definition of VaR

The VaR approach became more popular for bankers, regulators, consulting firms and academicians after the BIS Committee recognised it as one alternative for calculating banks' risk for capital adequacy purposes. Taylor (1993) defines VaR as the maximum amount that an institution can expect to lose on a given position during a given period or potential close-out period with a predefined probability. Chew (1996), Boudoukh (1997) and Hendricks (1996) define VaR as an approximation to the profit or loss generated by an institution due to changes in the market prices of underlying assets in a certain time horizon. Based on this definition, VaR contains the following features: (1) a position of underlying assets; (2) an estimate of the price volatility of underlying assets; (3) a time horizon or holding period.

In mathematical form, the risk of a position in a financial instrument is the following:
\[ \text{VaR}_{t+1|t} = V_t \sigma_{t+1|t} \]  

where,

\( \text{VaR}_{t+1|t} = \text{risk at time } "t" \)
\( V_t = \text{market value of the position at time } "t" \)
\( \sigma_{t+1|t} = \text{volatility of risk factors at time } "t" \text{ for the period } "t+1" \)

The equation above shows that the value of instruments is linearly related to the change of prices or rates. When the price of the underlying asset decreases by 2%, the value of the instrument decreases by 2%. However, the value of a financial instrument may not always be linear with respect to the change of prices. The best examples of this are options. The value of an option depends on the delta and the change of price of the underlying asset. Assuming the position is not linear and has a delta of 0.5, when the price decreases by 2%, the value of the instrument decreases by 2% \times 0.5 = 1\%. Finally, the mathematical form of VaR for a non-linear position is the following:

\[ \text{VaR}_{t+1|t} = V_t \sigma_{t+1|t} (\delta) \]  

where \( \delta \) is the delta of the option.

We need to go further to define the estimate of price volatility, the value of underlying assets, and the time horizon. Different parameters used in these three areas will produce different results.

We can also distinguish between Daily Earnings at Risk (DEaR) and VaR. DEaR is defined as an estimation of losses on a given portfolio that can be expected to be incurred over a single day, such as the next 24 hours, with a certain probability. VaR measures maximum estimated losses in market value of a given position that can be expected to be
incurred until the position can be neutralised or reassessed. If the time horizon is one day with a given probability level, then the VaR equals the DEaR.

Value at risk defines income as the net value of assets (i.e. after marking-to-market) and contracts held by a bank. The volatility of price or rate of an asset in the market (i.e. the net value of assets) may influence profit and loss. As defined in the previous section, the main purpose of VaR is to measure the maximum loss of a given portfolio in a certain time horizon at a given probability level. In VaR, we are just concerned with the probability of suffering loss. The crucial step in calculating VaR is to measure the loss which is derived from income volatility.

As part of risk management techniques, the banks’ managements tend to adjust their portfolios based on estimates of the changes of prices and rates. Therefore, risk estimation needs to follow two steps: (1) calculate the sensitivity of a portfolio to changes in underlying prices or rates; (2) estimate the potential changes in rates or prices. This sensitivity estimation is more important when the holding period of the VaR is longer. Figure 4.2 shows the procedure for calculating VaR.
4.3.2. Volatility assessment methodologies

According to Chew (1996, p.208) there are three methods to calculate volatility: the correlation method (i.e. variance/covariance matrix method), sometimes called the parametric method; historical simulation; and Monte Carlo simulation.

The correlation method calculates the change in the value of positions by combining the sensitivity of each asset to price changes, which are estimated by using variance/covariance matrices of the various component’s volatilities and correlations. This method uses the statistical assumption that the volatility (the change) of prices or rates is normally distributed. This study will adopt this method as the model is practical, and data is available from various data providers. Section 4.3.3 discusses in detail the parametric approach.
Simons provides a wider dimension of VaR by differentiating between simple historical and historical simulation as well as parametric (mean-variance analysis) and Monte Carlo simulation (Simons, 1996). The simple historical simulation method calculates the change in the value of positions by identifying the lowest returns (for example: 1%) from the range of returns in historical data and then multiplying the identified of the lowest returns by the current market value of a portfolio. The period of historical analysis plays a critical role in the accuracy of the results. A shorter period may not capture the whole variety of movements in prices or rates. The 1% of lowest returns is derived by establishing a rank of daily historical returns. The 1% of probability returns means that VaR is calculated using a 1% cut-off point from the lowest returns. According to Figure 4.3, the VaR of the 1% confidence interval is around 1.5%. This method is less complicated than the other methods. However, we would need to establish a huge data base for all portfolios of risk factors, and maintaining all the data is impractical. The problem is that not all the risk factor data is available. For example, a position of a forward exchange rate will entail volatility in the forward rate, yield volatility of currency 1, yield volatility of currency 2 and correlation of yield volatility of currencies 1 and 2.

Historical simulation calculates VaR by simulating the actual values of risk factors (interest rates, prices or exchange rates) in the past into current portfolio composition. By comparing the value of current portfolios and the value of portfolios derived from historical simulation, we can get the distribution of returns. The VaR can be calculated by employing confidence intervals identical to those defined in simple historical simulation. In historical simulation, we simulate the past portfolio returns by using the actual value of risk factors and the current portfolio composition instead of looking at the volatility of the actual portfolio returns.

The Monte Carlo simulation method calculates the change in the value of positions by using a random sample generated by price scenarios. Instead of using the past value of risk factors as mentioned in historical simulation, Monte Carlo simulation generates
models to estimate the risk factors from past portfolio returns by specifying the distributions and their parameters (i.e. volatility and correlation). Using these distributions and parameters, we can generate thousands of hypothetical scenarios for risk factors and, finally, we can determine future prices or rates based on hypothetical scenarios. VaRs can be derived from the cumulative distribution of future prices or rates for given confidence levels.

After studying the arguments, it is hard to say if one approach is better than the others without considering the specification of the position, the availability of data and information technology.

To determine which method is most appropriate, J.P. Morgan (1995, p.14) focuses on the answers to two questions. The first is whether the future price and rate movements are
normally distributed. If the future rate and price movements can be described in a statistical fashion by using simplifying parameters of a normal distribution, the volatilities and correlation method can be used. However, if market movements are not normal (e.g. for unexpected, sharp changes) the scenario approach will be appropriate. The second is whether the value of positions changes linearly with changes in rates and prices. If the change in the value is linear, we can use the position’s sensitivity to rate and price change (parametric). An option is an example of an instrument which contains a non-linear relationship between the change in the value and rate or price. As we know, the value of an option will be determined by whether the option is in or out of the money, and the future implied volatility is used in the pricing formula instead of the price or rate of the underlying asset. The scenario simulation, or full valuation approach, is more appropriate for non-linear positions. Based on the discussion above, there are two things that we need to consider in determining the ideal approach to calculating VaR: the distribution of portfolio returns and the linearity of the relationship between the value of the portfolio and the changes in rates and prices.

This study will focus on the parametric approach in calculating VaR because: (1) Most likely, the volatility of interest rates and foreign exchange rate returns up to July 1998 will follow a normal distribution as the government in Indonesia adopted a managed floating exchange rate policy. Additionally, the domestic currency interest rate is relatively stable. (2) The valuation of option positions will assume that their value changes linearly with changes in rates or prices (i.e. by using the measurement of Greek letters).

4.3.3. Parametric approach (delta valuation method)

In order to estimate price changes in the future, we need to characterise market movements statistically and derive a measure of estimated future “adverse” movement. Then, we apply the adverse movement to positions and compute the estimated resulting changes in market value.
From a series of daily historical prices or rates, we can identify the historical daily returns. Assuming $P$ is the price of a certain asset and "t" is time (daily), the daily price returns ($\Delta P_t$) are calculated from the following equation:

$$\Delta P_t = \ln P_t - \ln P_{t-1}$$ (4.5)

Based on the normal distribution assumption of the historical daily returns, we can estimate the volatility of price by using its mean ($m$) and spread of the delta prices around its mean value or standard deviation ($s$).

In a normal distribution, the probability that the volatility lies at a certain value depends on the mean ($\mu$) and the standard deviation ($\sigma$). According to Green (1993, p.58) and Griffiths, et al (1993, p.48) the probability density function of a normal distribution is calculated using the following formula:

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp \left[ -\frac{1}{2\sigma^2} (x-\mu)^2 \right]$$ (4.6)

where, $\mu =$ mean and $\sigma =$ standard deviation

The probability that an event lies within one standard deviation from the mean is 0.68. This statement can be written in the following mathematical form:

$$\mu - \sigma < X < \mu + \sigma = \int_{\mu-\sigma}^{\mu+\sigma} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} \, dr \approx 0.68$$ (4.7)

Additionally, we can also identify that the probability of an event lying within $1.65\sigma$ is 0.90; $1.96\sigma$ is 0.95 and in $2.57\sigma$ is 0.99.
To estimate the future volatility of prices or rates, we can adopt this rule by assuming an adverse movement will occur in certain confidence intervals (i.e. 0.90, 0.95 or 0.99). Assuming the mean of daily returns is 0.120% and the standard deviation is 1.40%, for an 0.90 confidence interval, the daily return will be in the range of 2.43% [i.e. 0.120% + (1.65 x 1.40%)] and -2.19% [i.e. 0.120% - (1.65 x 1.40%)]. For the purpose of value at risk, we consider just the case of negative return, or loss.

Therefore, risk estimation can be derived from the standard deviation\(^{12}\) of the delta prices by multiplying the estimate of delta price by the market value of assets. This treatment is true for a single portfolio which is sensitive only to price (single risk factor). For a single portfolio which is sensitive to price volatility and exchange rate volatility simultaneously, we need to consider the possible relationship between volatility of price and the exchange rates. For a portfolio of assets, risk estimation requires calculation of the risk relationship among portfolio investments (Markowitz, 1952, Sharp, 1970). The coefficient of risk relationship is between 0 and 1 and can be either positive or negative. Section 4.3.4.2 shows the detailed mathematical explanation of this theory. If we recall equation 4.2 from Section 4.2.2.4;

\[
\sigma_{AB} = \sqrt{\sigma_A^2 + \sigma_B^2 + 2\rho_{AB}\sigma_A\sigma_B} \quad (4.8)
\]

In a matrix notation, the daily diversified risk (DEaR) can be calculated as follows:

\[
DEaR = \sqrt{\mathbf{V}^\ast [C] \ast \mathbf{V}^T} \quad (4.9)
\]

where,

\(^{12}\) Variance (\(\sigma^2\)) is calculated from \(\frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X})^2\). Covariance (\(\sigma_{\text{cov}}\)) between A and B is calculated from \(\frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X}_A)(X_i - \bar{X}_B)\). Risk correlation between investment in A and B is calculated from \(\rho_{AB} = \frac{\text{Cov}_{AB}}{\sigma_A \ast \sigma_B}\).
\[ \tilde{V} = [DEaR_1, \ldots, DEaR_N] \rightarrow \text{It is the DEaR vector} \]

\[ [C] = \begin{bmatrix} 1 & \rho_{1N} \\
\vdots & \ddots \\
\rho_{N1} & \cdots & 1 \end{bmatrix} \rightarrow \text{It is the correlation matrix} \]

\[ V^T = \begin{bmatrix} DEaR_1 \\
\vdots \\
DEaR_N \end{bmatrix} \rightarrow \text{It is the transposed vector of V} \]

The matrix above can be solved using an EXCEL spreadsheet.

### 4.3.4. Identification of exposures

Before calculating the risk of a certain position, we need to identify the exposure of the position on a certain day when the risk is calculated. In general, the position consists of spot and forward elements. The identification of exposure for a spot position is straightforward: multiply the accounting value of the position by the market value or spot rate. In the case of forward positions, we will adopt the theory of economic value which has been discussed in the introductory chapter. Based on this theory, the value of the current position (economic value) is the net present value of the future cash flows. Technically, the process to identify the future cash flows of the positions is called mapping. However, there are some factors which influence the present value of forward positions such as discount factors, exchange rates, and prices.

This study will use the volatility of each relevant factor to calculate the present value of cash flows. For instance, if there are two cash in-flows of £100 for one and two months ahead, the present value is calculated based on the volatility of one-month and two-month yields.
In general, this study will adopt the valuation theories of financial instruments to calculate the current values of positions. Cash flow identification is the first step in risk valuation for forward positions. The objective of this process is to identify the risk factors (i.e. volatility and correlation) to which the cash flows are sensitive. The next step is to calculate the current exposures by discounting the future cash flows with current market rates. In the absence of interest rate references, such as LIBOR, SIBOR, etc., the current exposure can be derived by discounting future cash flows using a zero coupon rate. The following section discusses in detail each step using some examples.

In general, bank positions which are sensitive to market risks can be classified into four broad categories: fixed income (i.e. income is based on interest rate income), foreign exchange, equities and commodities. However, only fixed income and foreign exchange exposures are relevant for banks in Indonesia. The discussion below is thus limited to a consideration of fixed income and foreign exchange exposures.

4.3.4.1. Fixed income exposures

Earnings from a fixed income position depend on the amount to be paid, the period of repayment, and the performance of the payer (i.e. credit quality). In the discussion below, we exclude the performance of the payer. Banks normally use one of the following methods in order to identify the distribution of cash flows over time: (1) duration map; (3) principal map; and (3) cash flow map.

The duration map approach was invented by Macaulay (1938). This approach calculates an exposure by using the weighted average life of coupons and principal payments (for further detail see Chapter 5, section 3). The approach recognises the risk exposure according to duration. The principal map assumes that the exposure occurs at the payment date of the principal. Before the payment occurs, this position only appears in the off-balance sheet book. Earnings and risks are expressed by using the accrual basis of

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13 Banks in Indonesia are not allowed to perform transactions in equities or commodities.
valuation. When interest rates are volatile, this approach fails to represent the true earnings and risks. The cash flow map calculates the exposure based on the future stream of cash flows. However, this approach assumes that the expected flows are stable (i.e. no callable or puttable bonds).

To show the difference between the three maps, let us consider the position of a 10-year bond issued on 1 January 1994 with £1000 of nominal, 4.75% of half-yearly coupons, 11.44% of accrual yield to maturity and a market price of £900. From the above information, we can rewrite:

\[ C = £47.5 \text{ (i.e. } 4.75\% \times £1,000), \quad F = £1000, \quad P_0 = £900, \quad R = 11.44\% \text{ per year or } 5.72\% \text{ per half year and } N = 20 \text{ (half-year periods)}, \]

where \( C \) is coupon, \( F \) is future value, \( P_0 \) is current market value, \( R \) = yield (return) per year, \( N \) = the period.

Duration can be calculated as follows:

\[
D = \frac{C}{P_0} \left[ \frac{(1 + R)^{N+1} - 1(1 + R) - RN}{R^2 (1 + R)^N} \right] + \left[ \frac{F \times N}{(1 + R)^N} \right]
\]

\[
= \frac{47.5}{900} \left[ \frac{(1 + 0.0572)^{21} - 1(1 + 0.0572) - (0.0572 \times 20)}{0.0572^2 (1.0572)^{20}} \right] + \left[ \frac{1,000 \times 20}{(1.0572)^{20}} \right]
\]

\[
= 12.68 \text{ semi - annual periods, or } 6.34 \text{ years}
\]

This method identifies that the exposure occurs in 6.34 years’ time. The cash flow map identifies the exposure according to the future cash flows over time to expiration. Based on the above example, cash flows consist of £47.5 each half-year up to 9½ years and £1,047.5 at the maturity date. The principal map recognises the exposure only at the maturity date. Figure 4.4 shows the difference in risk exposure under the three approaches.
Figure 4.4.A

Cash flow map

Figure 4.4.B

Duration map
The cash flow approach provides the most accurate measure of risk (J.P. Morgan, 1994, pp. 106-110). The risk of a related position is calculated by multiplying the market value of the position by the prices’ or rates’ volatilities and correlations.

4.3.4.2. Exposures arising from foreign exchange positions

To re-value foreign exchange positions, all positions must be calculated in the base currency (Indonesian Rupiah or IDR). This section will discuss how to construct spot and forward foreign exchange positions. The coverage of foreign exchange positions includes all foreign exchange positions (i.e. both in the banking and trading books). A spot foreign exchange position is converted into IDR by using the spot rate on the day when the risk is calculated.

Forward foreign exchange positions cover all positions in forward agreements which exchange a certain amount of one currency for another at a future date. To calculate the
market value of the position, we ignore the transaction cost and risk premia. Holdings of purchased forward foreign exchange contracts represent long positions in the purchased currency and short positions in other currencies; in other words, lending a purchased currency and borrowing another currency. For example, purchasing a one year currency forward of 10 million US$/IDR means borrowing IDRs and lending US$ in one year’s time. To map the position, we need to know the IDR equivalent of USD 10 million on the maturity date using the forward rate. A forward rate is a term used to describe the market expectation about what the spot rate will be at the maturity date. One of the methodologies to estimate the forward rate is interest rate parity. This approach suggests that the forward rate depends on the interest rates of the two currencies and the spot exchange rate (Klopfenstein, 1993, p. 120). In mathematical form, the forward rate can be shown by the following equation:

\[
f_{T,t} = S_t \frac{(1 + r_{T,t}^{Foreign})}{(1 + r_{T,t}^{Domestic})}
\]

(4.11)

where,

- \(f_{T,t}\) = the forward rate observed at time \(t\), which locks in a spot rate at some future time \(T\).
- \(S_t\) = the spot rate observed at time \(t\).
- \(r_{T,t}^{Foreign}\) = the foreign interest rate, observed at time \(t\), for the time interval \(T-t\).
- \(r_{T,t}^{Domestic}\) = the domestic interest rate, observed at time \(t\), for the time interval \(T-t\).

To provide more detail concerning the forward rate, we can use the example below. Let us assume that the following information is given:

(The following information is the basic data for buying USD 100,000 forward)

- a. The spot rate of USD/IDR : 2,500 with price volatility of 0.975%
- b. USD yield per year : 6.0% with daily yield volatility of 1.25%
- c. IDR yield per year : 10.0% with daily yield volatility of 2.5%
- d. Maturity : 1 year
e. Nominal : USD 100,000
f. Risk correlation : see the following table (4.1)

### Table 4.1.
Risk Correlation Matrix

<table>
<thead>
<tr>
<th></th>
<th>USD/IDR</th>
<th>USD 1 year</th>
<th>IDR 1 year</th>
</tr>
</thead>
<tbody>
<tr>
<td>USD/IDR</td>
<td>1</td>
<td>0.0025</td>
<td>0.0050</td>
</tr>
<tr>
<td>USD 1 year</td>
<td>0.0025</td>
<td>1</td>
<td>0.10</td>
</tr>
<tr>
<td>IDR 1 year</td>
<td>0.0050</td>
<td>0.10</td>
<td>1</td>
</tr>
</tbody>
</table>

Using the above information, mapping can be performed by using the following procedure:

a. **Calculating the present value of the future cash inflow of USD 100,000**

   Based on the spot rates, the one-year yield of the two currencies, and the maturity, we can calculate the 1 year forward rate of USD/IDR =

   \[
   2500 \left[ \frac{(1 + 0.06*1)}{(1 + 0.1*1)} \right] = 2.623.76
   \]

b. **Calculating the future IDR position**

   IDR = 100,000 \times 2623.76 = 262,376,000

c. **Calculating price volatility**

   Price volatility of 1 USD:

   \[
   = \text{Volatility of USD yield} \times \text{Present value of interest on 1 USD received next year} \\
   = \text{Volatility of USD yield} \times \text{USD yield} \times \frac{\text{term}}{(1+\text{USD yield} \times \text{term})}
   \]

   \[
   = 1.25\% \times 0.06 \times \frac{1}{(1.06 \times 1)} = 0.0708\%
   \]

   Price volatility of IDR is calculated by using the same formula:

   \[
   = 2.5\% \times 0.1 \times \frac{1}{(1.1 \times 1)} = 0.2273\%
   \]
d. Identifying the positions

Risk in this transaction consists of four risk factors: the forward USD/IDR exchange rate, the USD yield volatility, the IDR yield volatility and correlations between these three. Each of the risks is associated with an exposure. The following table (4.2) shows the exposures of the risk factors:

<table>
<thead>
<tr>
<th>Risk</th>
<th>Position</th>
<th>Present value (current exposure)</th>
<th>Price volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>USD/IDR 1 year forward</td>
<td>(262,376,000)*</td>
<td>262,376,000x(1/1.1) = 238,523,636</td>
<td>0.975%</td>
</tr>
<tr>
<td>USD 1 year</td>
<td>100,000</td>
<td>100,000x(1/1.06) = 94,339</td>
<td>0.0708%</td>
</tr>
<tr>
<td>IDR 1 year</td>
<td>(262,376,000)*</td>
<td>262,376,000x(1/1.1) = 238,523,636</td>
<td>0.2273%</td>
</tr>
</tbody>
</table>

Note: *) Short position

e. Calculating risk

Risk of each risk factor is the product of price volatility and the current exposure. Based on the example above, the risk of each risk factor and diversified risk is as set out in the following table (4.3):
Table 4.3
Risk of a Forward Foreign Exchange Position

<table>
<thead>
<tr>
<th>Position</th>
<th>Calculation</th>
<th>Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>USD/IDR 1 year</td>
<td>((-238,523,636)\times(0.975/100)) = 2,325,605.45</td>
<td></td>
</tr>
<tr>
<td>USD 1 year forward</td>
<td>94,339*(0.0708/100)*2623.76 = 175,246.21</td>
<td></td>
</tr>
<tr>
<td>IDR 1 year</td>
<td>((-238,523,636)\times(0.2273/100)) = 542,164.22</td>
<td></td>
</tr>
<tr>
<td>DEaR</td>
<td></td>
<td>3,043,015.88</td>
</tr>
<tr>
<td>Diversified risk</td>
<td></td>
<td>2,327,179.39</td>
</tr>
</tbody>
</table>

Ignoring the risk correlation, the risk of the positions is IDR 3,043,015.88\textsuperscript{14}. By employing risk correlations, the diversified risk is IDR 2,327,179.39. The following discussion concerns the theory of risk in portfolios of positions.

4.3.4.3. Portfolio risk

The variance of a portfolio is defined as the expected value of the squared deviations of the returns for the portfolio from its mean expected return. Example: \(r_1\) = the return for asset 1, \(r_2\) = the return for asset 2, \(r_p\) = the return of the portfolio, \(w_1\) is the investment in asset 1 and \(w_2\) is the investment in asset 2.

\[
\sigma_p^2 = E\left[ r_p - E(r_p) \right]^2 = \left[ w_1 r_1 + w_2 r_2 \right] - \left[ w_1 E(r_1) + w_2 E(r_2) \right]^2
\]  \hspace{1cm} (4.12)

Grouping terms for the individual securities and factoring out the weights yields:

\textsuperscript{14} The risk exposure is calculated by summing the risks arising from the risk factors, whatever the sign (i.e. negative or positive).
\[ \sigma_p^2 = \left( \left\{ w_1 \left[ r_1 - E(r_1) \right] \right\} + \left\{ w_2 \left[ r_2 - E(r_2) \right] \right\} \right)^2 \]

Multiplying out, we obtain:

\[ \sigma_p^2 = w_1^2 \left( r_1 - E(r_1) \right)^2 + w_2^2 \left( r_2 - E(r_2) \right)^2 + 2w_1w_2 \left( r_1 - E(r_1) \right) \left( r_2 - E(r_2) \right) \]

where,

\[ \left( r_1 - E(r_1) \right) = \text{the standard deviation of expected returns on investment in asset 1 or } \sigma_1 \]
\[ \left( r_2 - E(r_2) \right) = \text{the standard deviation of expected returns on investment in asset 2 or } \sigma_2 \]
\[ \left( r_1 - E(r_1) \right) \left( r_2 - E(r_2) \right) = \text{the covariance between expected returns on investments in assets 1 and 2 or } \text{Cov}(r_1, r_2). \]

We can therefore express the equation above in the following form:

\[ \sigma_p^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1w_2 \text{Cov}(r_1, r_2) \quad (4.13) \]

We can measure the strength of covariance between two returns by using the correlation coefficient \( p_{1,2} \):

\[ p_{1,2} = \frac{\text{Cov}(r_1, r_2)}{\sigma_1 \sigma_2} \quad \rightarrow \quad \text{Cov}(r_1, r_2) = p_{1,2} \cdot \sigma_1 \sigma_2 \]

Finally, the portfolio variance for a two asset model, can therefore be restated as follows:

\[ \sigma_p^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1w_2 p_{1,2} \sigma_1 \sigma_2 \quad (4.14) \]

The variance of a three-security portfolio is:
\[ \sigma_p^2 = (w_i^1 \sigma_i^2 + w_i^2 \sigma_i^2 + 2 w_i^1 w_i^2 \rho_{i,j} \sigma_i \sigma_j) + (w_i^1 \sigma_i^2 - w_i^1 w_i^2 \rho_{i,j} \sigma_i \sigma_j) + (w_i^2 \sigma_i^2 - 2 w_i^1 w_i^2 \rho_{i,j} \sigma_i \sigma_j) \]

We can simplify into the following equation:

\[ \sigma_p^2 = \sum_{i=1}^{3} \sum_{j=1}^{3} \left( W_i^2 \sigma_i^2 + W_j^2 \sigma_j^2 + 2 \rho_{i,j} \sigma_i \sigma_j W_i W_j \right) \]  

(4.15)

From the exercise above, we obtain evidence that the result for diversified risk is lower than the result of the sum of individual risks (by assuming that risk correlation is +1). See section 4.2.2.4 for detail.

4.3.5. Problems with VaR

VaR models can provide a tool for management to control risk. With the VaR models, management can proxy the maximum of expected losses in a certain time horizon by employing a certain probability. The resulting VaR can be used to judge how to reallocate assets in a portfolio to achieve the desired risk level. However, the VaR may produce biased results and lead the management to make wrong decisions if several assumptions are not valid.

According to Chew (1996, pp.216-19) and Hopper (1996), the VaR methodology contains some pitfalls which create bias in risk estimation. First, the normality assumption in the parametric approach may create a bias in the risk estimate as the true distribution is not normal. Additionally the choice of confidence level is arbitrary.

Boudoukh (1997) argues that worst case scenarios provide precise measures in all cases and are more prudent. The distribution of returns may exhibit skewness (i.e. right or left) or kurtosis. The reason why the normality assumption is often used in quantitative analysis in finance is that the normal distribution has lots of useful statistical properties that make solving problems easy. Second, the VaR models exclude credit risk in their calculation,
especially for OTC derivatives. The true value of VaR will be higher if we incorporate credit risk into the calculation models. Third, the VaR assumes that all instruments can be settled at current market price. This assumption is not valid for illiquid assets which need to be sold at a discount. In this condition, the VaR provides biased information concerning the risk to portfolios. Fourth, the parametric approach employs volatilities and correlations which are derived from historical records. In other words, the VaR assumes that future returns will follow what happened in the past. If there is an extreme negative return, the VaR will fail to capture the event.

However, Zangari (1997) argues that we can capture event risk by employing a mixture of models, data and intuition, and using a stress test to test whether the model can capture event risk. Payant (1997) reported that the VaR method is still unclear concerning how risk is estimated, what risk factors and correlation should be included and how to validate the volatility and correlation estimate.

To account for these deficiencies, the Basle Committee on Banking Supervision introduced minimum qualitative and quantitative standards (see Appendix 4.8) for banks which intend to use internal models (BIS, 1996). Notwithstanding its weaknesses, VaR is the best risk management tool currently available to the banking industry and most multinational banks adopt VaR for internal risk management purposes.

4.4. The pre-commitment approach

Recognition of internal models in the BIS capital adequacy proposal (BIS 1996) is intended to measure banks' trading risks more accurately than if the BIS standardised methodologies were used. The use of internal models to calculate regulatory capital requirements thus addresses some of the pitfalls of the standardised methodologies of the BIS approach.
Internal models generally assess risks of trading positions using the estimates on a probability distribution of returns. Regulatory authorities use the risks to determine the probability of suffering losses and hence to determine the minimum capital adequacy requirements. Section 4.3 discusses internal models in more detail.

The Basle proposal (BIS, 1996) sets restriction on the statistical assumptions and sample period used for parameter estimation and the proportion of loss estimation that should be covered by capital. However, banks are free to set models to estimate the loss distributions.

The adoption of internal models in regulatory capital can provide consistent risk assessment between banks and regulatory authorities. The consistency doesn’t exist in some banks if regulatory capital is assessed using standardised methodologies because these banks have implemented internal models for risk management purposes. Kupiec and O’Brien (1995a) argue that an internal model is consistent with the regulatory concerns if the model satisfies the following requirements: (1) the accuracy of measurement of the internal model in measuring bank’s risk exposures can be achieved over a holding period which is addressed by regulators; (2) the bank’s model can be verified by regulatory authorities to ensure that the estimation accuracy of risks exists.

Using the parameters above, this discussion will examine whether the two condition exist in practice. Regulatory authorities suggest using 10 day holding periods (BIS 1996). The volatility of risk factors in trading are mostly in one day volatility - some of the instruments can even be broken down into intra-day volatility. Using the scaling method, which is called the “square root of T” (Smithson and Minton, 1996a; 1996b; and J.P. Morgan, 1996), the 10 day volatility ($V_{t=10}$) can be calculated from the one day volatility ($V_{t=1}$) using the following approach:

$$V_{t=10} = 10 \sqrt{V_{t=1}}$$

(4.16)
Scaling one day volatility into a longer period (e.g. 10 days) to set capital requirements to address regulatory concerns will reduce the accuracy of the models, especially for highly volatile risk factors (Christoffersen, et al, 1998).

Under the recognition of internal models, each bank will use its own model to estimate the volatility of risk factors. The verification by the regulatory authorities of internal models needs a benchmark to allow the former to conclude whether an internal model is providing under- or over-estimates. However, to determine which model should be used as a benchmark should ideally be accomplished by comparing all available models in the banking industry, with the most accurate model being considered as the benchmark. However, if the benchmark model is believed the most accurate one, it is not necessary to allow banks to use their internal models; the benchmark model could be adopted as the universal model for all banks.

Given these difficulties, the pre-commitment approach (PCA) to setting minimum capital adequacy over a given time horizon may give a better solution (Kupiec and O'Brien, 1995c). The approach allows banks to pre-commit to ensuring that their losses do not exceed the limits which they have committed themselves to. Penalties will be applied if the losses break the pre-committed level.

Kupiec and O'Brien (1995c) suggest one way to calculate penalties, based on the per dollar of excess loss, using the following equation:

\[ P = \frac{1+r}{F(-C^*)} \]  

where,

\[ P \] = the dollar penalty for each dollar loss in excess of the committed capital  
\[ r \] = the bank's weighted average cost of capital  
\[ C^* \] = the capital commitment chosen by the banks
Chapter 4 - Capital Adequacy Assessment with Respect to Market Risk

\[ F(-C^*) = \text{the cumulative probability that the commitment is breached} \]

This approach assumes that the average cost of capital is constant over time.

To follow up this suggestion, the US Federal Reserve Board requested public comment on the PCA for setting market risk capital requirements. Most of the responses suggested the continued development of PCA, and the New York Clearing House organised a pilot study of PCA. The participating institutions responded that the PCA is, indeed, appropriate as an alternative to the internal model approach for determining the capital adequacy of trading activities, and that further steps should be taken to refine and ultimately implement the PCA (Considine, 1998).

In contrast, Gumerlock (1996) argues that the PCA doesn’t protect against a "go-for-broke strategy", such as that adopted at Barings (Clifford, 1995). After the PCA has been approved, the only monitoring from regulatory authorities concerns whether the accumulation of losses breaks the pre-committed capital. If the accumulated losses exceed the level of pre-committed capital, banks will pay penalties. However, regulatory authorities have no right to force banks to reduce their exposures when the banks’ accumulated losses are approaching the level of the pre-committed capital. Banks have the right to carry on trading regardless of the size of the exposure since the accumulative losses are still within the level of pre-committed capital.

A policy of Stop-loss is definitely required in an event such as the stock market crash of 1987. However, Kupiec and O’Brien (1996) argue that most “go-for-broke strategies” are not part of company strategy, but very much related to fraud. Internal controls can play a major role in this regard. Further, they mention that neither the PCA nor the internal model approach can protect an institution against the breakdown of its internal controls.

The debate concerning the PCA very much depends on the capability of banks’ management to set up accurate internal models for risk assessment and the capability of banks’ internal controls to prevent excessive trading positions. If both conditions are
considered as satisfactory from a regulatory authority point of view, PCA may be favoured over the internal models approach. The problem, however, is how capable are regulatory authorities in assessing the accuracy of the internal models and the capability of internal controls in banks to prevent fraud.

PCA is less applicable for banks which are operated and located in developing countries because banks in those countries mostly have weak (or even no) risk assessment systems, including internal control systems. Implementation of PCA in developing countries may thus create moral hazard for banks, inducing them to adopt “go-for-broke” strategies. However, the PCA may encourage banks to develop risk management units to control their risks. This study, however, believes that the PCA is appropriate only for banks which adopt sophisticated risk management models.

4.5. Conclusions

The Basle Accord of 1988 focuses on credit risk only. The Accord does not take into account other risks which affect banks' profit volatility (i.e. price risk, interest rate risk, foreign exchange risk, and operational risk). Furthermore, there are also some deficiencies in the approach adopted towards the measurement of bank risk. This suggests that the methodology adopted to assess bank risk for capital adequacy purposes requires further examination.

The discussion in this chapter has shown that there are many approaches available for calculating market risk. The BIS proposal provides for simple and practical calculations, including the use of internal models which have been adopted by most multinational banks. From a theoretical point of view, the proposal produces inaccurate measures of risk as a result of simplification and false assumptions of exposure and risk factors. Simplification of the calculation of exposure, approximations for volatility and exclusion of volatility correlations are the main pitfalls of the BIS proposal.
Use of VaR models is an alternative to the standardised method. However, VaR also contains some weaknesses which may provide biased information concerning bank risk. The normality assumption and choice of confidence interval are among the factors which may produce biased information about bank risk. By using the normality assumption, VaR fails to capture shock events (outliers) in the volatility measure. Furthermore, the results vary depending on the probability level which is used in the model. The key issues in VaR are two-fold: how to identify risk exposure and how to estimate the volatility of risk factors. The next step in this study contains modelling and empirical work to assess the foreign exchange rate risk arising from the foreign exchange positions run by one of the banks - the biggest forex player - in Indonesia.

It is unclear whether the BIS standardised proposal is more accurate and suitable as the basis for minimum capital adequacy regulation around the world than VaR. However, the BIS’ s standardised proposal is more practical and simple. Hence, the BIS proposal can be used widely by both modern and traditional banks. But, the standardised proposal will produce less accurate measures than those deriving from the use of VaR if sophisticated derivatives operations are undertaken.

One of the alternative methodologies which could be used to assess the adequacy of capital for banks is the PCA. However, the PCA is less applicable for banks in Indonesia for two main reasons: (1) banks in Indonesia have not yet adopted risk management models; (2) banks in Indonesia have less stringent internal control systems in relation to the monitoring of exposures and the prevention of fraud. Therefore, this study concludes that the introduction of the PCA in Indonesia might induce banks to adopt “go-for-broke” strategies.
Chapter 5

Literature Review of Financial Instruments and Risk Evaluation Methodology

5.1. Introduction

Market risk mostly occurs in positions of trading in financial instruments and derivatives. This chapter will outline the definitions of several types of financial instruments, including pricing methodologies, and apply VaR to assess the risks of holding the positions in those instruments. The main purpose of this discussion is to identify the best risk evaluation methodology for the financial instruments and derivatives for VaR purposes. This chapter will be organised in the following way: Section 5.2 discusses swaps; Section 5.3 discusses bonds; Section 5.4 discusses forward rate agreements (FRAs) and futures; Section 5.5 discusses options; Section 5.6 discusses equities; Section 5.7 concludes the discussion.

5.2. Swaps

5.2.1. Basic concept of swaps

Swap transactions occur as a result of three possible conditions; different expectations for price or rate movements, different purposes with regard to the positions of banks (i.e. either hedging or market making) and comparative advantages in access to the capital markets (Marshal, 1996, p.3, Tucker, 1994, pp.489-513). Figure 5.1. shows the basic format of an interest rate swap:
Swaps can be exchanged both in markets (i.e. on the organised exchanges) and over-the-counter (OTC). The organised markets provide swaps with certain standardised contracts which do not always meet the needs of swap users. However, the users can make swap contracts with other banks or brokers to include specific terms in the contract. Due to these needs, the plain vanilla swaps can be modified by using the appropriate terms to suit the specific end user’s need. The objective of conducting swaps is two fold: to make money and to protect the position from risk (hedge).

The following sub-sections discuss the evaluation methodology for interest rate swaps and currency swaps. The evaluation methodology for commodity swaps and equity swaps is similar to that for interest rate swaps and currency swaps. For this reason, this subsection does not discuss commodity and equity swaps.

5.2.2. Risk evaluation methodology for interest rate swaps

Marshal (1993, p.48) suggests that there are many factors which can influence the value of swaps; maturity, structure of the swaps, the availability of a counterparty, the number and the price of asset substitutions for hedging purposes, creditworthiness of counterparty,
demand and supply for credits in general and swaps in particular in countries where currencies are involved in the swaps, and the regulatory limitations on the flow of capital that can influence the efficiency of the market.

For the purposes of the discussion in this sub-section, the maturity and the structure of swaps are the only factors to be considered in the swap valuation. The discussion ignores the other factors suggested by Marshal.

Based on figure 5.1, we can make a simple calculation to show the role of the reference rate in affecting the value of swaps for both counterparties. If the LIBOR semi-annually increases to 7.1% per year, the counterparty will lose 0.1% as the interest rate differential between 7.0% fixed and LIBOR floating. However, the counterparty may make money when LIBOR semi-annually drops to the point below 7.0% p.a. For risk calculation purposes, attention is focused on the volatility of LIBOR semi-annually.

To indicate the role of volatility in interest rate swap valuations, this sub-section considers various types of swaps. The following example shows that a swap may also be used to transform a funding position in order to reduce cost, under the assumption that the two counterparties have different estimates for the movement of interest rates.

Assume there are two counterparties: A and B (i.e. with different credit ratings) who want to transform their funding positions in order to reduce the risks arising from the volatility of LIBOR. Because of the different credit ratings, they can access the money market at different interest rates. Assume counterparty A (i.e. with an AAA rating) can obtain funds from the money market at a fixed interest rate of 7.5% per year and a floating interest rate of LIBOR + 30 bps. Counterparty B can obtain funds from the money market only at higher interest rates (i.e. 8.2% p.a. fixed rate and LIBOR + 70 bps floating). Counterparty A assumes that interest rates will increase in the future and the management of company A decides to take 7.5% fixed rate funding. The management of company B assumes that the interest rate will drop and management decides to take LIBOR + 70 bps.
The two companies may transact a swap to reduce their funding costs. The flow of funds in this swap can be mapped as shown by Figure 5.2.

When the two companies decide to transact a swap, company A will pay a floating rate (LIBOR) and receive fixed while company B will pay fixed and receive a floating rate (LIBOR). The negotiation occurs between the two parties to decide the fixed rate. In fact, there are many scenarios in which to negotiate the price of the swap. Assume that a 7.4% p.a. fixed rate is agreed between the two parties. The benefit of the swaps is shown in Table 5.1.
### Table 5.1
Benefit of Swap Transactions

<table>
<thead>
<tr>
<th>Fixed</th>
<th>Net payment of company A</th>
<th>Benefit of company A</th>
<th>Net payment of company B</th>
<th>Benefit of company B</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.5%</td>
<td>Libor</td>
<td>0.3%(Libor+30bps)</td>
<td>8.2%(7.5%+(Libor+70bps-Libor))</td>
<td>8.2%-8.2%= 0%</td>
</tr>
<tr>
<td>7.4%</td>
<td>Libor+10bps(7,5% -7.4% + Libor)</td>
<td>0.2%(Libor+30bps)-(Libor+10bps)</td>
<td>8.1%(7.4%+(Libor+70bps-Libor))</td>
<td>8.2%-8.1%= 0.1%</td>
</tr>
<tr>
<td>7.3%</td>
<td>Libor+20bps(7.5% -7.3%+Libor)</td>
<td>0.1%(Libor+30bps)-(Libor+20bps)</td>
<td>8.0%(7.3%+(Libor+70bps-Libor))</td>
<td>8.2%-8.0%= 0.2%</td>
</tr>
</tbody>
</table>

From the examples above, the volatility of interest rates clearly plays an important role in the valuation of interest rate swaps (yields). Based on the liquidity premium theory\(^\text{15}\), the yields of debt instruments are directly related to their price sensitivity to interest rate fluctuations (Blake, 1990, p.47-51). The longer the maturity of the debt instruments, the higher the premiums (i.e. higher interest rates) required. However, other factors such as the frequency of coupon payments and the credibility of the issuers may also influence the yields. There are many varieties of interest rate swaps such as basis swaps, forward swaps, amortising swaps, etc. However, these are not discussed in this section.

### 5.2.3. Risk evaluation methodology for currency swaps

A currency swap generally contains three components of cash flow: exchange of initial principal at the spot rate when the contract is begun; exchange of interest payments; and re-exchange of the principal at the spot rate agreed at the beginning of the contract. In

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\(^{15}\) The liquidity premium theory explains that the shape of the yield curve represents the interest rate risk. The longer the maturity, the higher the interest rate is.
fact, the basic idea of a currency swap is just an exchange of borrowing between two counter-parties. By using currency swaps, users may get benefits from the following opportunities: (1) enables investors or borrowers to access a wider market place to get lower costs of funds without assuming additional currency risk; (2) provides an opportunity to hedge the assets internationally; (3) trading purposes.

To provide a clear understanding of currency swaps, we can use the following example: Counterparty A enters into a fixed/fixed US$/JPY cross currency swap for 3 years. It is agreed that interest is paid/received annually at 5% for JPY and 6% for US$. From this example, we can illustrate the exchange of payments between the two counter-parties as shown by Figure 5.3.

---

**Figure 5.3.**

**Cash Flows of Currency Swaps**

- **Initial exchange of principal**
  - A \(\rightarrow\) B
  - Yen 10 billion
  - $100 million

- **Interest payments**
  - A \(\rightarrow\) B
  - $6\%
  - Yen 5%

- **Repayment of principal**
  - A \(\rightarrow\) B
  - $100 million
  - Yen 10 billion

---
Assume that the spot rate of US$/JPY = 100, the cash flow of counter-party A can then be shown in the following table:

### Table 5.2.
### Cash Flows of Counterparty A per Currency

<table>
<thead>
<tr>
<th></th>
<th>US$ cash flows (in US$ million)</th>
<th>JPY cash flows (in Yen billion)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Spot</strong></td>
<td>100</td>
<td>(10)</td>
</tr>
<tr>
<td><strong>Year 1</strong></td>
<td>(6)</td>
<td>0.5</td>
</tr>
<tr>
<td><strong>Year 2</strong></td>
<td>(6)</td>
<td>0.5</td>
</tr>
<tr>
<td><strong>Year 3</strong></td>
<td>(106)</td>
<td>10.5</td>
</tr>
</tbody>
</table>

Valuation of swaps positions can be performed by transforming future cash flows into present values by using estimates for discount factors and forward exchange rates. Assume that the estimates for discount factors are as shown by Table 5.3 and the forward exchange rates are derived using the interest rate differential approach (see Chapter 4).

### Table 5.3.
### Assumed Discount Factors and Forward Exchange Rates

<table>
<thead>
<tr>
<th></th>
<th>US$ DF</th>
<th>Yen DF</th>
<th>US$/Yen Forward</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Year 1</strong></td>
<td>100%</td>
<td>100%</td>
<td>97</td>
</tr>
<tr>
<td><strong>Year 2</strong></td>
<td>94%</td>
<td>95%</td>
<td>95.9789* )</td>
</tr>
<tr>
<td><strong>Year 3</strong></td>
<td>88%</td>
<td>90%</td>
<td>94.8444</td>
</tr>
</tbody>
</table>

Note:

* ) 95.9789 is an estimate of the forward US$/Yen at year 2 by using estimated discount factors (DF) of US$ and Yen (i.e. 97 x (94/95)). The same treatment is used for the forward US$/Yen at year 3.
Based on these estimations for DFs and US$/Yen forward rates, we can calculate the value of the swap after the cash flow of year 1 had been paid for by counterparty A, who has dollar-based currency, as follows:

**Yen flows (billion):**
- Year 2: Present value of Yen flow 0.5 x 95% = Yen 0.475 billion
- Year 3: Present value of Yen flow 10.5 x 90% = Yen 9.450 billion

Dollar equivalent of Yen flows at 97 spot rate = US$ 102.32 million

**Dollar flows (million):**
- Year 2: Present value of dollar flow (6) x 94% = US$ (5.64) million
- Year 3: Present value of dollar flow (106) x 88% = US$ (93.28) million

**Swap value at year 1 in US$:** (102.32-93.28-5.64) = US$ 3.4 million

From the above example, it can be seen that the value of a currency swap depends on the volatility of interest rates and forward exchange rates.

Finally we can conclude that the risk associated with swaps may occur as a result of volatility in interest rates, exchange rates or prices of instruments or commodities depending on the type of swaps. Sometimes, the risk in swaps depends on the combined volatility amongst interest rates, exchange rates and prices of assets or financial instruments as a result of the volatility relationship between them.

### 5.2.4. Application of VaR to swaps

Before we begin to measure the risks involved in swaps, we need to know the basic information which is required for risk evaluation. The basic information varies depending on the type of swaps. To simplify the discussion, we use an example of a plain vanilla interest rate swap. The detail of this example is shown in Table 5.4 and detailed discussion of the VaR is outlined in Chapter 4.
The basic information required of the position is as follows: the nominal of swaps, the basis for the fixed leg and the floating leg, the maturity of the swaps, the zero rate curve of the floating currency up to the maturity of the swaps, the price volatility of the zero curve and the risk correlation of zero rate coupons. We apply zero coupon rates (i.e. normally government bonds) as discount factors in calculating present values because the zero coupon rates are free from credit risk premiums. The risk calculation of a swap position using VaR involves the following procedure: first, calculate the forward yield to estimate the floating payment using the zero curve; second, calculate the cash flows of the floating leg based on the estimated forward yield; third, calculate the net present value of the future cash flows; fourth, calculate the VaR by employing the data for price volatility and risk correlation. Table 5.4 shows the detailed calculation.
### Table 5.4

Value at Risk for Swaps

1. **Basic data**
   - Interest rate swap US$: 1,000,000
   - Fixed leg: 9.379%
   - Floating leg: yearly USD-Libor
   - Maturity: 5 years

2. **Market data and risk correlation estimates**

<table>
<thead>
<tr>
<th>Year</th>
<th>Zero Curve</th>
<th>Price Volatility</th>
<th>1 yr</th>
<th>2 yr</th>
<th>3 yr</th>
<th>4 yr</th>
<th>5 yr</th>
<th>Forward Curve</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.75%</td>
<td>0.10%</td>
<td>1</td>
<td>0.93</td>
<td>0.92</td>
<td>0.93</td>
<td>0.92</td>
<td>1-f-0 0.088</td>
</tr>
<tr>
<td>2</td>
<td>9.08%</td>
<td>0.23%</td>
<td>0.93</td>
<td>1</td>
<td>0.99</td>
<td>0.99</td>
<td>0.97</td>
<td>1-f-1 0.094</td>
</tr>
<tr>
<td>3</td>
<td>9.24%</td>
<td>0.36%</td>
<td>0.92</td>
<td>0.99</td>
<td>1</td>
<td>0.9</td>
<td>0.98</td>
<td>1-f-2 0.096</td>
</tr>
<tr>
<td>4</td>
<td>9.34%</td>
<td>0.47%</td>
<td>0.93</td>
<td>0.99</td>
<td>0.9</td>
<td>1</td>
<td>0.99</td>
<td>1-f-3 0.096</td>
</tr>
<tr>
<td>5</td>
<td>9.42%</td>
<td>0.55%</td>
<td>0.92</td>
<td>0.97</td>
<td>0.98</td>
<td>0.99</td>
<td>1</td>
<td>1-f-4 0.097</td>
</tr>
</tbody>
</table>

3. **Cash flow profile**

<table>
<thead>
<tr>
<th>Year</th>
<th>Cash flow fixed</th>
<th>Present value</th>
<th>Net Cash flow</th>
<th>Price Volatility</th>
<th>VAR</th>
<th>USD swap correlation</th>
<th>Horizontal vertex</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fixed Float</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-93794 87,500</td>
<td>-86,247 80,460</td>
<td>-5,788</td>
<td>0.10%</td>
<td>6.0</td>
<td>1 0.93 0.92 0.93 0.92</td>
<td>6.0 0.62 5.01 8.64 12.76</td>
</tr>
<tr>
<td>2</td>
<td>-93794 94,110</td>
<td>-78,829 79,094</td>
<td>266</td>
<td>0.23%</td>
<td>0.62</td>
<td>0.93 1 0.99 0.99 0.97</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-93794 95,607</td>
<td>-71,950 73,341</td>
<td>1,391</td>
<td>0.36%</td>
<td>5.01</td>
<td>0.92 0.99 1 0.9 0.98</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-93794 96,405</td>
<td>-65,623 67,451</td>
<td>1,827</td>
<td>0.47%</td>
<td>8.64</td>
<td>0.93 0.99 0.9 1 0.99</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-93794 97,406</td>
<td>-59,799 62,101</td>
<td>2,303</td>
<td>0.55%</td>
<td>12.76</td>
<td>0.92 0.97 0.98 0.99 1</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>VaR</td>
<td>33.04</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>DEaR</td>
<td>13.65</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5.3. Bonds

5.3.1. Basic concept of bonds

We can recognise many types of bonds such as straight bonds (or plain vanilla bonds), zero coupon bonds, convertible bonds, and many other types of bonds. The difference mainly depends on the issuers (i.e. government or corporate), the way of paying interest (i.e. zero coupon, fixed coupon, index-linked, and income bonds), and the redemption term (i.e. callable bond, perpetual bond, convertible bond). In general, a bond is a promise from an issuer to bondholders that the issuer will pay amounts of money (nominal and coupons) in the future to bond holders. However, income bonds will pay the coupon only when the bond issuer earns enough profit. Sometimes, the repayment of nominal (the redemption date) is not specified as the redemption date will be decided by the issuer in the future (i.e. callable bond) or the bond has no maturity (perpetual bond). In this case, the coupon is paid indefinitely. Below we limit the discussion to bonds with a fixed maturity for both coupon and zero coupon bonds.

5.3.2. Risk evaluation methodology for bonds

The discussion in this part focuses on the risk associated with holding bonds. There are a number of factors which may affect the price of bonds in the market. In general, we can classify the risk of holding bonds into a specific and a general market risk. Even though the risk factors of a general market risk may vary (due to inflation risk, political risk, interest rate risk, etc), this sub-section focuses on the general market risk with respect to interest rate risk. There are two approaches to measuring interest rate risk for fixed income instruments: the duration method and the convexity method.

5.3.2.1. Duration method
The duration method is the most popular method used to approximate the rate of sensitivity of bond prices to interest rate changes. The BIS proposal for capital regulation with respect to market risk (BIS, 1996) also refers to this approach in order to approximate interest rate risk for debt securities. The duration method was invented by Macaulay (1938). He defines duration as the weighted average maturity of a bond using the relative discounted cash flows in each period as weights. In mathematical terms, duration can be expressed in the following equation:

\[
D = \frac{d}{P_d} \sum_{t=1}^{T} \frac{t}{(1 + rm)^t} + \frac{B}{P_d} \frac{T}{(1 + rm)^T} \tag{5.1}
\]

where,

- \(D\) = duration
- \(d\) = annual coupon
- \(B\) = par value of bond
- \(P_d\) = dirty price of bond (i.e. market price)
- \(t\) = time in year to \(t^{th}\) cash flow
- \(T\) = time in years to maturity
- \(rm\) = yield to maturity

In qualitative terms, the formula above says that the duration of a bond can be calculated from the relative present value of future cash flow to the current price of the bond in absolute terms.

From the equation above, we can also derive the value of a zero coupon bond and a perpetual bond. A zero coupon bond will have \(d=0\), therefore:

\[
D = \frac{B}{P_d} \frac{T}{(1 + rm)^T} \tag{5.2}
\]
The relationship between duration and maturity is shown by Figure 5.4.A and the relationship between duration and yield is expressed by Figure 5.4.B.

**Figure 5.4**
Relationship Between Duration and Maturity and Yield

Figure 5.4.A shows the relationship between duration and term to maturity of different types of bonds. In a perpetual bond (i.e. a bond without maturity date), $T$ is indefinite ($\infty$) and the duration is calculated merely from the current yield ($d/P_0$) regardless of the term of maturity. In other words, the bond is not sensitive to the term of maturity. If the dirty price is below the par value, the duration will be higher. Alternatively, if the dirty price is above the par value, the duration is lower. Figure 5.4.B shows the relationship between the duration and yield. The duration has a negative slope with respect to yield. Normally, investors will prefer lower duration as a result of less sensitivity to volatility of interest rates. The lower duration implies that there is a low response of the bond value to the change of interest rate. In practice, most financial analysts use modified duration (MD) to analyse the sensitivity of bond prices to interest rates:
\[ MD = \frac{-D}{(1 + rm)} \] (5.3.)

The modified duration can be interpreted as approximating the percentage change in the price of a bond resulting from a 1% change of interest rates in the next instant in time. Additionally, the relationship between the bond price (Pd) and the yield to maturity can be explained by Figure 5.5.
Figure 5.5 shows that duration is the slope of the dirty price of the bond with respect to the yield to maturity. The changes of the dirty price can be solved using the following procedure (Strong, 1993, pp.52-96; Diacogiannes, 1995, pp.431-56):

$$P_d = \sum_{i=1}^{r} \frac{d}{(1+rm)^t} + \frac{B}{(1+rm)^r}$$  \hspace{1cm} (5.4)

Changes in the price of bonds can be derived from the first order derivative:

$$\frac{\Delta P_d}{\Delta(1+rm)} = -d \sum_{i=1}^{r} \frac{t}{(1+rm)^{t+i}} - B \frac{T}{(1+rm)^{r+i}}$$

Multiplying both sides by \((1+rm)/P_d\), we obtain the following equation:

$$\frac{\Delta P_d}{P_d} \frac{\Delta(1+rm)}{P_d} = -d \sum_{i=1}^{r} \frac{t}{(1+rm)^{t+i}} - B \frac{T}{P_d (1+rm)^{r+i}} = -D$$

$$P_d = -D * \frac{\Delta(1+rm)}{(1+rm)} * P_d$$

*Note: * is the sign of multiplication

Based on the above model, interest rates and time play important roles in bond valuations. However, the model excludes credit risk in the valuation. In the case of coupon bonds, credit risk is one of the most important determinants in valuation.

### 5.3.2. 2. Convexity method

Sometimes, analysing a bond’s price using modified duration is not enough because the yield change is not constant. Assume we have already calculated modified duration from certain changes of yield. However, the modified duration will be inaccurate when there is continuous movement of yield. Therefore, we need to adjust the modified duration which has been calculated by employing the second order derivative of the sensitivity of price changes against the change of yield (Yawitz, 1989; Sullivan and Kiggins, 1989). The objective of the application of the second order derivative is to improve the accuracy of the measurement of the bond’s price sensitivity given modified duration.
By employing the Taylor expansion series, the second order of differential with respect to \( rm \) of equation 5.4 can be calculated in the following equation ( Ostaszewski, 1993, pp. 384-410):

\[
\frac{\Delta P_d}{P_d} = \frac{1}{P_d} \frac{\Delta P_d}{\Delta rm} (\Delta rm) + \frac{1}{2P_d} \frac{\Delta^2 P_d}{\Delta rm^2} (\Delta rm)^2
\]

\[
= -MD(\Delta rm) + \frac{C}{2} (\Delta rm)^2
\]

where,

\( MD = \) modified duration

\( C = \) convexity

Duration and convexity of a bond with maturity at \( T \) and coupon \( d \) paid at \( t \) can be solved in the following equation:

\[
P_d = \sum_{t=1}^{T} \frac{d}{(1 + r)^t} + \frac{B}{(1 + r)^T} \\
= \left[ \sum_{t=1}^{T} d * (1 + r)^{-t} \right] + \left[ B(1 + r)^{-T} \right]
\]

\[
\frac{\Delta P_d}{\Delta rm} = \left[ \sum_{t=1}^{T} -t * d * (1 + r)^{-(t+1)} \right] + \left[ -T * B(1 + r)^{-(T+1)} \right]
\]

\[
\frac{\Delta^2 P_d}{\Delta rm^2} = \left[ \sum - (t + 1) * -t * d(1 + r)^{-(t+2)} \right] + \left[ - (T + 1) * -T * B(1 + r)^{-(T+2)} \right]
\]

To give a clearer overview of the convexity, we will use a portfolio consisting of: a £100 two-year bond that pays 5% coupon semi-annually, a £103 dirty price and an 8% yield to maturity. The price and cash flow pattern will be:
Chapter 5 - Literature Review of Financial Instruments and Risk Evaluation Methodology

\[ P_d = 5 \times (1.04)^{-1} + 5 \times (1.04)^{-2} + 5 \times (1.04)^{-3} + 5 \times (1.04)^{-4} + 100 \times (1.04)^{-4} = 103.6299 \]

\[ \frac{\Delta P_d}{\Delta rm} = -1 \times 5 \times (1.04)^{-2} - 2 \times 5 \times (1.04)^{-3} - 3 \times 5 \times (1.04)^{-4} - 4 \times 5 \times (1.04)^{-5} - 4 \times 100 \times (1.04)^{-5} = 371.55 \]

Duration = \[ \frac{37154}{103} = 3.6 \text{ semi-annually or 1.8 yearly} \]

\[ \frac{\Delta^2 P_d}{\Delta rm^2} = 2 \times 5(1.04)^{-3} + 6 \times 5(1.04)^{-4} + 12 \times 5(1.04)^{-5} + 20 \times 5 \times (1.04)^{-6} + 20 \times 100 \times (1.04)^{-6} = 1743.510 \]

Given that the price of the bond is 103.6299, convexity is \((1/2) \times (1743.510/103.6229) = 8.4122\).

This result is the convexity of the bond during two years. To quote the convexity on a yearly basis, we can divide the convexity for two years by the square of the frequency of bond payment per year. In this case, the payment is twice per year. The convexity per year is \(8.4122/(2^2) = 2.1031\).

### 5.3.3. Application of VaR to bonds

Duration and convexity measure the sensitivity of a bond’s price to yield changes. This implies that the duration and convexity are concerned only with interest rate risk. However, the risk of investment in bonds is not only interest rate risk, but also foreign exchange risk when the bond is denominated in foreign currency. Therefore, the duration and convexity are unable to cover foreign exchange risk arising from exchange rate volatility. A VaR model can provide a more comprehensive measurement of risk. The detail for the VaR calculation for a bond position is shown in Table 5.5. This sub-section excludes discussion of procedures showing how to apply VaR to bond positions because the technique is similar to that demonstrated for swaps. Detailed discussion of the VaR is outlined in Chapter 4.
### Chapter 5 - Literature Review of Financial Instruments and Risk Evaluation Methodology

#### Table 5.5
Value at Risk for Bonds

1. **Basic data on 25 April 1995**
   - US's ABC bond (US$) 100,000
   - Maturity Apr-00
   - Coupon per year 10.0%

2. **Risk factors:**
   2.1. US$ yield volatility for 1 year, 2 years respectively up to 5 years
   2.2. Risk correlation among the yields

3. **Cash flow exposures**

<table>
<thead>
<tr>
<th>Year</th>
<th>Cash flow</th>
<th>Cum-cf</th>
<th>Term</th>
<th>US Yield</th>
<th>PV</th>
<th>Cum-PV</th>
<th>MD *)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25-Apr-96</td>
<td>10000</td>
<td>10000</td>
<td>1</td>
<td>7.0555</td>
<td>9,341</td>
<td>9,341</td>
<td>(0.873)</td>
</tr>
<tr>
<td>25-Apr-97</td>
<td>10000</td>
<td>20000</td>
<td>2</td>
<td>7.2836</td>
<td>8,688</td>
<td>18,029</td>
<td>(1.287)</td>
</tr>
<tr>
<td>25-Apr-98</td>
<td>10000</td>
<td>30000</td>
<td>3</td>
<td>7.4017</td>
<td>8,072</td>
<td>26,101</td>
<td>(1.689)</td>
</tr>
<tr>
<td>25-Apr-99</td>
<td>10000</td>
<td>40000</td>
<td>4</td>
<td>7.5428</td>
<td>7,476</td>
<td>33,577</td>
<td>(2.076)</td>
</tr>
<tr>
<td>25-Apr-00</td>
<td>110000</td>
<td>150000</td>
<td>5</td>
<td>7.6344</td>
<td>76,144</td>
<td>109,71</td>
<td>(3.628)</td>
</tr>
</tbody>
</table>

4. **Data volatility and correlation**

<table>
<thead>
<tr>
<th></th>
<th>1 year</th>
<th>2 years</th>
<th>3 years</th>
<th>4 years</th>
<th>5 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield Vol.</td>
<td>3.16</td>
<td>2.104</td>
<td>1.735</td>
<td>1.63</td>
<td>1.503</td>
</tr>
<tr>
<td>Current yield</td>
<td>7.038</td>
<td>7.275</td>
<td>7.391</td>
<td>7.536</td>
<td>7.628</td>
</tr>
<tr>
<td>Price volatility</td>
<td>0.208</td>
<td>0.267</td>
<td>0.315</td>
<td>0.378</td>
<td>0.415</td>
</tr>
<tr>
<td>Correlation Matrix</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 year</td>
<td>1</td>
<td>0.881</td>
<td>0.809</td>
<td>0.782</td>
<td>0.737</td>
</tr>
<tr>
<td>2 years</td>
<td>0.881</td>
<td>1</td>
<td>0.985</td>
<td>0.955</td>
<td>0.916</td>
</tr>
<tr>
<td>3 years</td>
<td>0.809</td>
<td>0.985</td>
<td>1</td>
<td>0.983</td>
<td>0.952</td>
</tr>
<tr>
<td>4 years</td>
<td>0.782</td>
<td>0.955</td>
<td>0.983</td>
<td>1</td>
<td>0.991</td>
</tr>
<tr>
<td>5 years</td>
<td>0.737</td>
<td>0.916</td>
<td>0.952</td>
<td>0.991</td>
<td>1</td>
</tr>
</tbody>
</table>

5. **VaR**

<table>
<thead>
<tr>
<th>Year</th>
<th>PV</th>
<th>Price Vol</th>
<th>VaR</th>
<th>Horizontal Vertex</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>9,341</td>
<td>0.208</td>
<td>19.41</td>
<td>19.41</td>
</tr>
<tr>
<td>2</td>
<td>8,688</td>
<td>0.267</td>
<td>23.22</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>8,072</td>
<td>0.315</td>
<td>25.42</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>7,476</td>
<td>0.378</td>
<td>28.42</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>76,144</td>
<td>0.415</td>
<td>315.98</td>
<td></td>
</tr>
<tr>
<td>VaR</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DEaR</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*) MD = modified duration
5.4. Forward rate agreements (FRAs) and futures

5.4.1. Basic concept of FRAs and futures

The FRA contract is designed to meet the needs of both parties in terms of size, maturity and currency. This contract is less marketable because the design of the contract is suitable just for the specific needs of the two companies. This instrument is not traded in regulated markets. Therefore, credit risk in forward contracts is the most significant component of risk (see Blake, 1990, pp.158-9; Kolb, 1997, pp.1-25).

Sometimes it is difficult to distinguish between futures and forward contracts. The main difference is that futures contracts can only be traded in regulated markets while forward rate agreements are designed to suit only the two counterparties (see Tucker, 1994, pp. 399-441; Shapiro, 1991, pp.113-6). Therefore, the futures contract has specific characteristics. The detail of the differences between futures and FRAs is shown in Table 5.6. In general, there are three types of futures contracts: (1) stock index futures; (2) interest futures; and (3) currency futures. The objective of doing these transactions is to speculate in the price of instruments (making money), arbitrage or hedge certain positions. Futures instruments include interest rate futures contracts, such as futures contracts in 90 day eurodollar time deposits, 30 day US Federal Funds, 90 day US Treasury bills, Eurosterling time deposits, bonds 20 year US Treasury Bonds, 10 year US Treasury notes and other government bonds.
### Table 5.6
Differences Between Futures and FRAs

<table>
<thead>
<tr>
<th>Futures</th>
<th>FRAs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Transaction is conducted through regulated</td>
<td>1 Transaction is conducted according to the</td>
</tr>
<tr>
<td>market.</td>
<td>agreement between two parties.</td>
</tr>
<tr>
<td>2 Terms of conditions in the contract are</td>
<td>2 Terms of conditions in the contract are</td>
</tr>
<tr>
<td>standardised.</td>
<td>designed to meet specific needs of the</td>
</tr>
<tr>
<td></td>
<td>parties.</td>
</tr>
<tr>
<td>3 Credit risk is negligible since the</td>
<td>3 Credit risk is important to price.</td>
</tr>
<tr>
<td>regulated market is responsible for the</td>
<td></td>
</tr>
<tr>
<td>settlement and imposes daily loss margin.</td>
<td></td>
</tr>
<tr>
<td>4 Daily mark-to-market approach is more</td>
<td>4 Current value is difficult to identify</td>
</tr>
<tr>
<td>appropriate to evaluate the positions.</td>
<td>since there is no active market for the</td>
</tr>
<tr>
<td></td>
<td>specific design of FRAs.</td>
</tr>
</tbody>
</table>

#### 5.4.2. Risk evaluation methodology for FRAs and Futures

The value of forward and futures contracts will be zero on the date of the beginning of the contracts. At the expiration date, the value of the contracts equals the difference between the contract price and the spot price at the expiration date. When the spot price at the expiration date is lower than the contract price, the buyer loses and the seller benefits. Further calculation is required when we evaluate the value of the contract prior to expiration. Tucker (1994, p.431) suggests that the price of a forward or futures contract at the time to expiration is the difference between the spot price at the date of valuation and the present value of the forward or future contract over the remaining time to the expiration. Assume that the forward or future price on the contract is £1000, the current spot price is £900, the zero coupon yield is 10% per year, and the remaining time to expiration is 5 years. The current value of the forward or futures contract is:
\[
= \frac{1000}{(1 + 0.1)^5} \\
= 620.92
\]

The current value of the contract is £900 - £620.92 = £279.08 From this example, we can identify that the value of the contract depends on the spot price and the volatility of the yield over the time to expiration.

5.4.3. Application of VaR to FRAs and futures

To evaluate the risk of FRAs and futures in VaR models, we will adopt the cash flow approach for fixed incomes and foreign exchange positions as defined in section 2. The following outline is the procedure for calculating risk in FRAs and futures: (1) identify the risk factors of the fixed income position (i.e. price and foreign exchange); (2) identify the cash flow exposure of each risk factor (i.e. if the position contains forward exchange, the foreign exchange forward can be calculated by using the current spot rate and yield); (3) calculate the present value of all cash flow exposures; (4) employ the volatility of risk factors and correlations in order to obtain the VaR. Tables 5.7 and 5.8 show examples of how to apply VaR to forward contracts. Detailed discussion of the VaR is outlined in Chapter 4.
Table 5.7
Value at Risk for Forward Rate Agreements (FRAs)

1. Basic data
   1.1. Buying 6x12 FRA Fr 1,000,000  
       (borrowing Fr which begins 6 months from now for period of 12 months on a  
       discount basis and investing the proceeds for 12 months)
   1.2. Forward yield for 1 year 7.2365%  
       \[
       \left(1 + \frac{6.93\% \times 365}{365}\right)\left(1 + \frac{6.39\% \times 182}{365}\right) - 1 \times \frac{365}{365-182}
       \]
   1.3. Current 6 months yield is 6.39% and 12 months yield is 6.93%

2. Yield volatility and correlation
<table>
<thead>
<tr>
<th>Yield Vol</th>
<th>Price Vol</th>
<th>Correlation matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 mths</td>
<td>6.94</td>
<td>0.21</td>
</tr>
<tr>
<td>12 mths</td>
<td>7.42</td>
<td>0.48</td>
</tr>
</tbody>
</table>

3. Mapping of cash flows and calculating VaR

<table>
<thead>
<tr>
<th>Maturity (days)</th>
<th>Cash flows</th>
<th>Rate</th>
<th>Market value</th>
<th>Vertex</th>
<th>Yield Volatility</th>
<th>Price Volatility</th>
<th>VaR</th>
<th>Correlation Matrix</th>
<th>Horizontal Vector</th>
</tr>
</thead>
<tbody>
<tr>
<td>182</td>
<td>1,000,000</td>
<td>6.39%</td>
<td>969,121.40</td>
<td>6 Months</td>
<td>6.94</td>
<td>0.21</td>
<td>2,081</td>
<td>1</td>
<td>2,081 4,662</td>
</tr>
<tr>
<td>365</td>
<td>1,036,282</td>
<td>6.93%</td>
<td>969,121.40</td>
<td>12 Months</td>
<td>7.42</td>
<td>0.48</td>
<td>4,662</td>
<td>0.7</td>
<td>1</td>
</tr>
</tbody>
</table>

VaR 6,743.5
DEaR 3,335.3
### Table 5.8
Value at Risk for Forward Foreign Exchange

<table>
<thead>
<tr>
<th>1. Basic data</th>
<th>2. Risk data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Term (in year)</td>
<td>Yield % Yield Volatility % Price Volatility</td>
</tr>
<tr>
<td>Currency 1: DEM</td>
<td>DEM/USD</td>
</tr>
<tr>
<td>Currency 2: USD</td>
<td>DEM 1 year</td>
</tr>
<tr>
<td>F/X spot rate: 1.540</td>
<td>5.6900 1.380 0.0007</td>
</tr>
<tr>
<td>DEM yield: 5.688%</td>
<td>DEM 1 year</td>
</tr>
<tr>
<td>USD yield: 6.188%</td>
<td>6.1900 1.980 0.0012</td>
</tr>
<tr>
<td>DEM position: 153,000,000</td>
<td>DEM 1 year</td>
</tr>
<tr>
<td>DEM/USD forward rate: 1.53274871</td>
<td>DEM 1 yr (0.0035) 1.000 0.1240</td>
</tr>
<tr>
<td>USD 1 yr: 1.53274871</td>
<td>USD 1 yr (0.0042) 0.124 1.0000</td>
</tr>
</tbody>
</table>

#### 3. Position of USD
- USD position in one year later: 99,820,667.9400
- Present value of USD position: 94,003,717.9

#### 4. Mapping of positions

<table>
<thead>
<tr>
<th>Period</th>
<th>Future cash flows</th>
<th>Present Value</th>
<th>VaR</th>
<th>Horizontal Vertex</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM/USD</td>
<td></td>
<td>94,003,718</td>
<td>905,256</td>
<td>905,256</td>
</tr>
<tr>
<td>DEM 1 yr</td>
<td>1 year</td>
<td>153000000</td>
<td>144,765,726</td>
<td>70,170</td>
</tr>
</tbody>
</table>
| USD 1 yr | 1 year | (99,820,670.00) | (94,003,718) | 108,496.9
|        |       |               | VaR | 1,083,923 |
|        |       |               | DEaR | 904,905 |
5. 5. Options

5.5.1. Basic concept of options

In an option contract, a company may want to sell assets to hedge against adverse movements in the prices of the underlying assets. The party can hedge the position of the underlying asset by buying a put option. If the price in the market drops below the price shown on the option contract, the company will exercise the put option. This condition is called the option buyer being “in the money”. In this case, one party (the buyer or owner) buys a put option (to sell assets) and another party (the writer) writes a put option to buy assets. The decision on whether the options will be exercised lies in the hands of the buyers of the options. In another example, a party may want to buy assets to hedge against adverse movement in the price of the underlying assets. If the price of the asset in the market is more expensive than the price on the contract, the party will exercise the option. In this case, one party (the buyer or owner) buys a call option (to buy assets) and another party (the writer) writes a call option to sell assets. The decision on whether the option will be exercised lies in the hands of the buyers of the options.

The value of an option may be “in the money”, “at the money” or “out of the money”. From the option buyers’ point of view, a put option is in the money when the strike price is above the sum of the market price plus premium and a call option is in the money when the strike price is below the sum of the market price plus premium. From the buyers’ point of view, a call option is at the money when the strike price is the same as the sum of the market price plus premium, and out of the money when the strike price is below the sum of the market price plus premium. From the call buyer’s point of view, a call option will be out of the money when the strike price is above the sum of the market price plus premium.

Figure 5.7 shows the four kinds of options using graphs and Figure 5.8 shows the value of a call option.
Figure 5.6.
Type of Options

- **Call buyer (buying asset)**
  - Profit
  - Break-even
  - Limited loss (premium)
  - Unlimited profit

- **Call writer (selling asset)**
  - Profit
  - Break-even
  - Limited profit (premium)
  - Unlimited losses

- **Put buyer (selling asset)**
  - Profit
  - Strike price
  - Limited loss (premium)
  - Unlimited profit

- **Put writer (buying asset)**
  - Profit
  - Strike price
  - Limited profit (premium)
  - Unlimited losses
5.5.2. Risk evaluation methodology for options

There are many approaches available for valuing options. The most common approaches are: put-call parity relationship; Black-Scholes model; binomial tree; and the sensitivity analysis using Greek letters. The discussion below focuses on the option valuation using the above models and concludes by suggesting which is the best approach to be used in empirical studies.

5.5.2.1 Put-call parity relationship

The put-call parity relationship model was designed just to price European options (i.e. options which can be exercised only on the maturity date and on which no dividend
payment is made). This approach suggests that the value of an European put option should be equal to the combined value of a call option on one share of the same stock with the same strike price and time to expiration, a short position of one share of underlying stock, and a riskless investment of an amount equal to the present value of the strike price (Cox, 1985, p.42). As a mathematical expression, we can show this in the following equation:

\[ P = C + K \exp^{-rt} - S \]  \hspace{1cm} (5.6)

where,

- \( P \) = current market price of a European put option to sell one share
- \( C \) = current market value of a European call option to buy one share
- \( r \) = riskless interest rate covering the life of the option
- \( t \) = time to expiration of the put (and call) option
- \( K \) = strike price for the put (and call) option
- \( S \) = current market price of the underlying stock

The above equation can be modified into the following equation to calculate the value of a call option:

\[ C = P + S - K \exp^{-rt} \]  \hspace{1cm} (5.7)

Deviation of market price from this relationship creates opportunities for market participants to make profit from a zero risk investment through arbitrage under the assumption that there are no transaction costs, margins or taxes. For example, when call prices are too high relative to put prices, market participants can perform the following transactions: (1) selling a call option; (2) buying a put option of the same underlying instrument with the same strike price and time to expiration; (3) estimating the present value of the strike price using a risk-free interest rate as a discount factor and the period of time to expiration \( "t" \ (K \exp^{-t}) \); (4) buying underlying assets.
On the maturity date, the borrowing fund will be replaced by the funds which are obtained from put settlement if the price in the market lies below the strike price. Written call options will not be exercised by the buyers as a result of a lower market price compared to the strike price. It means the arbitrageur can benefit from the difference between the premium received from selling call options and premium paid for buying put options. Alternatively, the arbitrageur can create profit when the put price is too high relative to the call price by buying calls, selling put, borrowing the amount of $K \exp^{-\sigma}$, and buying underlying assets.

Table 5.9 below shows the cash flows of options transactions which generate zero net cash flows and where the arbitrager will receive zero profit if the premium received from selling a call option equals the amount paid for buying options.

<table>
<thead>
<tr>
<th>Current cash flow</th>
<th>At expiration date</th>
<th>$S^* \leq K$</th>
<th>$S^* &gt; K$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Write call</td>
<td>$C$</td>
<td>0</td>
<td>$K - S^*$</td>
</tr>
<tr>
<td>Buy put</td>
<td>$-P$</td>
<td>$K - S^*$</td>
<td>0</td>
</tr>
<tr>
<td>Buy stock</td>
<td>$-S$</td>
<td>$S^*$</td>
<td>$S^*$</td>
</tr>
<tr>
<td>Borrow</td>
<td>$K \exp^{-\sigma}$</td>
<td>$-K$</td>
<td>$-K$</td>
</tr>
<tr>
<td>Net</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note: $S^*$ is the market price at the maturity date

The put-call parity relationship approach can also be applied in future options. In the case of stock options, initial investment is required to buy or sell a stock. In the futures options, investment is not necessary to construct a portfolio. Therefore, there is no borrowing of funds in futures option portfolios. The put-call parity relationship equation for futures options can be shown in the following formula:
\[ P_f = C_f + K - F \]  

where,

- \( P_f \) = market price of put future
- \( C_f \) = market price of call future
- \( K \) = Strike price
- \( F \) = Future price

The call parity relationship valuation model is an appropriate tool for determining the price of options, especially for arbitragers who intend to make profit from the different premiums between put and call options. However, this model is less applicable for institutions which hold the option positions for hedging purposes. Additionally, the model is unable to provide information concerning the risk of option positions - instead it suggests that the values of option positions change linearly with the changes in the prices of put or call options and the prices of the underlying assets.

### 5.5.2.2. Black-Scholes model

This model was developed by Fisher Black and Myron Scholes in 1973 (Black-Scholes, 1973). The model was originally designed for European options on non-dividend-paying stocks. Now, the model has been used for other options such as futures options, foreign exchange options, and debt security options, as well as for American options.

According to Black-Scholes, the value of a call option on a risk-free portfolio which consists of a long call option and a short position in the underlying stock can be shown in the following equation:
\[ C = SN(d_1) - K \exp^{-rt} N(d_2) \]  
\[ d_1 = \frac{\ln(S/K) + rt + 0.5\sigma^2 t}{\sigma \sqrt{t}} \]  
\[ d_2 = d_1 - \sigma \sqrt{t} \]  

where,  
\( C \) = the value of call option  
\( S \) = market price of underlying asset  
\( K \exp^{-rt} \) = present value of the strike price discounted by using the risk-free interest rate  
\( r \) = risk-free interest rate  
\( t \) = time to expiration  
\( \ln(.) \) = natural logarithm  
\( N(.) \) = the cumulative probability distribution function for a standardised normal variable  
\( \sigma \) = the annual volatility of stock returns or standard deviation of stock returns.

The model is applicable given the following conditions: (1) the underlying asset cannot pay discrete dividends or accrue interest payments; (2) the option being valued is a European option (i.e. it cannot be exercised before the expiration date); (3) the risk-free interest rate is constant over the life of the option; (3) the underlying asset returns are normally distributed with constant mean and standard deviation; (4) all asset markets are perfectly efficient, with continuous trading and zero transaction costs and no taxes; (5) the short selling of securities with full use of proceeds is permitted.

The Black-Scholes model can be applied in risk-free portfolios which consist of futures options and underlying futures contracts (Gemmill, 1993, pp.180-200). Unlike in stock options, this position does not require any initial investment and there is no return. Based on this condition, Black-Scholes (1976) developed the futures option pricing formula in the following equation:
\[ C_f = \text{Exp}^{-\mu t} \left[ FN(d_1^*) - KN(d_2^*) \right] \]
\[ d_1^* = \frac{\ln(F/K)}{\sigma_f \sqrt{t}} + 0.5\sigma_f \sqrt{t} \]
\[ d_2^* = d_1^* - \sigma_f \sqrt{t} \]

This formula uses the same assumptions as those used for stock options.

The Black-Scholes approach is simpler than the binomial approach because the Black-Scholes model contains a one-step solution rather than a multi-step solution. Additionally, computation in the Black-Scholes model is faster than in the multi-period solution. The main criticism of this model is associated with the normality assumption of the distribution of the underlying asset returns. If the true distribution of underlying asset returns is skewed or exhibits kurtosis, the price estimations of options will be biased. Additionally, the Black-Scholes model is applicable only for European options where the exercises occur at the maturity dates.

5.5.2.3. Risk-neutral valuation

The risk-neutral valuation approach assumes that the composition of a portfolio consists of one unit of assets and a short call option. According to Cox, Ross and Rubinstein (1979), the return on the portfolio is certain irrespective of the price of the underlying assets. As the return is certain, the return must be a risk-free return. This approach requires the assumption that the price of underlying assets moves up and down to a certain level on the maturity date. To illustrate this condition, we use the following example: (1) a portfolio consists of assets worth £100; (2) after time \( t \), the assets will be worth either £110 or £90; (3) the strike price of selling the call (writing call) option is £100; (4) the current price of the asset is £100. According to Gemmill (1993, p.51), the portfolio yields a risk-free interest return since the number of options equals 1/hedge ratio (see the next example). The hedge ratio can be derived from the following equation:

\[ hSU - (SU - K) = hSD - (SD - K) \]
where,

- $h$ = hedge ratio
- $U$ = market price which goes up to a certain level
- $D$ = market price which goes down to a certain level
- $K$ = exercise price
- $S$ = share price of assets

The equation above shows that whatever the price moves, the portfolio will give the same return.

To simplify this equation, we will use "cu" for $(SU - K)$ and "cd" for $(SD - K)$

Rearranging the equation above we can solve for "$h$" with the following:

$$hSU - cu = hSD - cd$$
$$hSU - hSD = cu - cd$$
$$h = \frac{cu - cd}{S(U - D)}$$

Based on the example above, we can calculate the hedge ratio with the following result:

$$h = \frac{(110 - 100) - (90 - 100)}{1(110 - 90)} = \frac{10}{20} = 0.5$$

In other words, we have a risk-free portfolio of assets to short calls in the ratio of 1:2. If the portfolio comprises 1 asset and 2 options (i.e. 1/0.5 where 0.5 is the hedge ratio), it will always be worth £90. If the price increases to £110, buying one share and selling one call will be worth £100 (£110-£10) where £110 is the price of one share and -£10 is the value of selling a call (i.e. we sell to the call buyer at strike price, £100, while the market price is £110). However, if the number of selling calls is 2, the value of the portfolio will be £90 (£110-£20). If the price falls, the position will be worth £90 (£90-0) where £90 is the price of one share and 0 is the value of selling a call because the buyer will not
exercise the option. By buying a number of calls twice the number of unit assets, we will be free from adverse movements in the price of underlying assets.

The following scenario, which consists of 0.5 units of assets and one call, will generate the same result regardless of the price. If the price rises, the value of the option equals 45 [i.e. (0.5*110)-10]. Alternatively, if the price falls, the value of the option equals 45 [i.e. (0.5*95)-0].

As we discussed in the previous section, this hedge position will pay the risk-free rate of interest charged on borrowing funds to buy an asset. Therefore, we can construct the relationship between gross pay-off (i.e. the amount of money which is received from the investment in the portfolio) and the risk-free rate of interest with the following equation:

\[ 1 + r = \frac{\text{gross pay-off}}{\text{investment}} \]  

(5.12)

By using the example above, the gross pay-off is 45 and the investment is the current price of the asset minus the call premium [(0.5*100)-c]. With a certain risk-free rate of interest, we can calculate the value of a call option:

\[ 1 + 0.05 = \frac{45}{0.5(100) - c} \]
\[ 45 = 1.05(50 - c) \]
\[ 45 = 52.5 - 1.05c \]
\[ 1.05c = 52.5 - 45 \]
\[ 1.05c = 7.5 \]
\[ c = 7.15 \]

This approach demonstrates its ability to value the position of an option by assuming that the institution's main strategy is to avoid risk.
5.5.2.4. The binomial tree

The binomial option pricing model calculates the value of options by assuming that the prices of assets move in a multiplicative binomial process over discrete periods. It means that "S" moves up to "u" and down to "d" by a specific amount in the next period. The value of "u" at $t_0$ equals 1 and the value of the asset at $t_1$ will either be "uS" or "dS" where "u" > 1 and 0 < d < 1 (Cox et al., 1979). If we choose "u" as a symbol of the multiplier by which the price moves up, the downward price multiplier will be $\frac{1}{u}$. This rule is necessary to ensure that the return of holding certain assets is symmetric. Detailed illustration of the value of the portfolio at a period of $t_1$ is shown in Table 5.10.

<table>
<thead>
<tr>
<th>Period of $t_0$</th>
<th>Up/down</th>
<th>Period of $t_1$ (up)</th>
<th>Period of $t_1$ (down)</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underlying asset (S)</td>
<td>Up</td>
<td>&quot;uS&quot;</td>
<td>-</td>
<td>&quot;p&quot;</td>
</tr>
<tr>
<td></td>
<td>Down</td>
<td>-</td>
<td>&quot;dS&quot;</td>
<td>(1 - p)</td>
</tr>
<tr>
<td>C (option)</td>
<td>Up</td>
<td>$C_u = \text{Max}(0, uS - K)$</td>
<td>-</td>
<td>&quot;p&quot;</td>
</tr>
<tr>
<td></td>
<td>Down</td>
<td>-</td>
<td>$C_d = \text{Max}(0, dS - K)$</td>
<td>(1 - p)</td>
</tr>
</tbody>
</table>

The call option buyer will let the option be un-exercised when the market price of the underlying asset gives no benefit for the buyer (i.e. the option is "out of the money") and

16 Example: the price movements are 100, 110 and 100, the percentage of movement at the end of period 1 is 10/100=10% and at the end of period 2 is -10/110=-9.099%. The absolute movement is 10 units of price. However, the movement in percentage is different as a result of the different denominators (i.e. 10% and -9.099%). To get symmetric results, we can use ln110/100=0.0953 and ln 100/110=-0.0953. From this example, we can also state that if the price rises to uS (100x1.1) and falls to S/u (100/1.1), then the returns will be ln uS/S and ln (S/u/S) or log1/u.
will exercise the option when the market price is higher than the exercise price. Therefore, there are two conditions of the option's value: either 0 or \((uS - K)\). To employ this model, we need to know the probability that the price of the underlying asset moves up or down at period \(t_1\). We can indicate the probability by using the following formula (Cox and Rubenstein, 1985, pp.169-74):

\[
p = \frac{\exp^{-r - d}}{u - d}, \text{ or } \\
1 - p = \frac{u - \exp^{-r}}{u - d}
\]

Equation (5.13)

Additionally, we can also calculate \(u\) by employing the expected volatility \(\sigma\) or \(u = e^\sigma\). Normally the volatility is expressed on a yearly basis. To calculate \(\sigma\) in intended time, we can multiply yearly \(\sigma\) by square root of \(t\) or \(u = e^{\sigma \sqrt{t}}\). For example: monthly volatility equals \(u = e^{\sigma \sqrt{1/12}}\). To get the value of an option at period \(t_0\), we can use the present value of \(C_u\) and \(C_d\) by employing the risk-free discount rate:

\[
C = \left[pC_u + (1 - p)C_d\right]^{-n}
\]

Equation (5.14)

To illustrate the application of this model, we employ a position of a call option. An American call option on a zero-yielding asset with current asset price \(S = 100\); strike price \(K = 100\); risk-free rate of interest \(r = 10\%\); volatility \(\sigma = 20\%\); \(T = 1/4\) (3 months). Assume we calculate the binomial pricing model using a two-step tree, the possible asset prices at months 1 and 2 can be expressed in the following calculation:

\[
u = e^{\sigma \sqrt{1/12}} = 1.0577; \quad d = 1 / u = 0.9454; \quad p = \frac{1.01 - 0.9454}{u - d} = \frac{0.0646}{0.1123} = 57.52\%
\]
\[ C_u = \max[0, (105.77 - 100)] \]
\[ = 5.77 \]
\[ C_d = \max[0, (94.54 - 100)] \]
\[ = 0 \]
\[ C = [0.5752 \times 5.77 + (1 - 0.5752) \times 0] \times \left( \frac{1}{1 + \frac{0.1}{12}} \right) \]
\[ = [3.3189] \times 0.9918 \]
\[ = 3.2917 \]

Figure 5.8 shows the various possible prices of one unit of asset in the first and second period.

**Figure 5.8**

*Two-step Tree of Binomial Valuation*

![Two-step Tree of Binomial Valuation Diagram]

Figure 5.9 shows the possible values of the underlying asset in periods 1 and 2 with the assumption that the price in period 2 also follows the same binomial process. The possible price at the end of period one is either 105.77 (\(uS\)) or 94.54 (\(dS\)). In a multi-period binomial model, \(uS\) and \(dS\) probably go up or down with the same probability as those in period 1. The "\(uS\)" may go up to "\(uuS\)" or down to "\(udS\)" and "\(dS\)" may go up to
"udS" or down to "ddS". The value of an option can be represented in the following figure (Figure 5.9):

**Figure 5.9**
Framework of Option Valuations Using the Binomial Tree

In the second year, we have three alternatives for the value of C. The value of C in period 2 can be solved by using the following procedure:

1. \( C_u = \frac{pC_{uu} + (1-p)C_{ud}}{1+r} \)

2. \( C_d = \frac{pC_{du} + (1-p)C_{dd}}{1+r} \)

3. \( C = \frac{pC_u + (1-p)C_d}{1+r} \)

Replacing \( C_u \) and \( C_d \) in equation 3, we can solve for C.
We can expand the application of the binomial tree into multiple periods by using the same properties. The more periods we employ, the more the model provides alternative values of the option. However, this model requires the following assumptions: (1) the "u" and "d" multipliers are the same in all periods; (2) there are no transaction costs (in other words, hedging can be established for each period between the options); (3) the asset has no sunk cost; (4) interest rates are constant; and (5) there is no dividend payment. The model also requires too many calculations, particularly for calculation of the multi-period tree.

The binomial tree can be applied to American options since we employ the tree with interval periods until the maturity date of the options. However, the binomial tree is computationally demanding when the number of tree-steps is high and it is impractical if we try to apply it to daily tree-steps. Additionally, this model employs price volatility to identify whether the price moves up or down within certain levels. Since the price volatility is derived from the procedure by assuming that the distribution of option returns is normal, the assumption violates the fact that the true distribution of returns is not always normal.

5.5.2.5. Sensitivity of option premium

To evaluate the option position, we can also employ sensitivity analysis of the option premium to various factors which are used to calculate the premium. As mentioned in the
previous section, option prices are influenced by the following factors: price volatility, time to expiration, and interest rates. In this sub-section, we will discuss option valuations using option premium sensitivity with respect to these factors (i.e. the "Greek letters"). Then, the change in value of an option can be derived from the multiplication of the sensitivity (i.e. delta, gamma, vega, rho, etc) and the change of the factors for which the sensitivity is calculated. For instance, for the change of the value of an option with delta 0.5 and a change of the price of underlying asset \((X - S)\), where "X" represents the estimated value of the future price of the asset and S represents the current spot price of the underlying asset, the value of the option is calculated from: 

\[ 0.5 \times (X - S) \]

The current value of an option \( (V) \) equals the previous value of an option \( (V_0) \) plus the change in the value of the option \( (dV) \) or \( V = V_0 + dV \). The following section will discuss in more detail the sensitivity of option premiums.\(^{17}\)

5.5.2.5.1 Delta (\( \Delta \))

Delta measures the sensitivity of the call prices to the volatility of the share price. In mathematical terms,

\[
\delta = \frac{\partial V}{\partial S} \bigg|_{t_0} \tag{5.15}
\]

where,

- \( V \) = the value of the option,
- \( S \) = the value of the underlying instrument (share price), and
- \( \delta \) is the delta, \( \partial V \) is the change in the option’s value, \( \partial S \) is the change in the price of the underlying assets, and \( V_0 \) is the value of the option in period \( t_0 \). Additionally, \( \partial S = (X - S) \).

\(^{17}\) The sources of information concerning the Greek letters in this section is derived from Merton (1990, pp. 177-278), Gemmil (1993, pp. 72-9), and Strong (1993, pp. 340-60).
Rearranging the equation above, we can solve for $\mathcal{N}$:

$$\mathcal{N} = \delta \cdot \mathcal{S}$$

Since we already know the delta and the estimated future price of the underlying asset by using price volatility, we can calculate the change in the value of an option (i.e. the risk of holding an option). In the Black-Scholes model, the delta is simply the $N(d_1)$ and the sensitivity of the put price to the share price is $N(d_1) - 1$. A delta of 0.6 means that the call price will move to 0.6 if the price of the share increases by 1. To establish a fully hedged position, a fund manager will buy the number of call options equal to the number of shares divided by the delta. If the share position is 60 units, the full hedge position of options must be $60/0.6 = 100$ calls.

### 5.5.2.5.2. Gamma ($\Gamma$)

Sometimes the delta fails to measure the option value as a result of linear approximation. To get a better approximation of the value of options, we can also use the second order derivative of the change of an option’s value with respect to the share price (i.e. the gamma). The gamma of an option measures the change of an option’s delta with respect to the underlying asset’s price. In mathematical terms, we can express this using the following equation:

$$\Gamma = \left. \frac{1}{2} \frac{\partial^2 V}{\partial S^2} \right|_{S_0}$$

The Black–Scholes model identifies this gamma as the following term:

$$\frac{N'(d_1)}{S \sigma \sqrt{t}}$$

where $N'(d_1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}d_1^2}$

A gamma of 0.10 means that delta will increase by 0.10 when the asset price increases by one unit. The put gamma will simply be the negative of the call gamma.
5.5.2.5.3. **Theta (Θ)**

Theta is the sensitivity of the option premium to the time to maturity. A theta measures the movement of option premium in a particular period. A 10% daily theta of an option to maturity means that the option premium will decline by 0.1 between today and tomorrow assuming that all other factors remain the same. This condition implies that the value of an option is less valuable as the time to expiration decreases. The following equation is the mathematical representation of theta:

\[
Q = \frac{\partial V}{\partial t}
\]  

(5.17)

The Black-Scholes model identifies theta in the following term:

\[
\left[ \frac{S_0}{2\sqrt{t}} \right] N'(d_1) + Ee^{-rT}N(d_2)
\]

5.5.2.5.4. **Vega (Λ)**

Vega measures the change in the option’s price with respect to the change in the volatility of the price of underlying assets. A vega of 0.3 indicates that a one percentage point increase in price volatility produces a 0.3 unit change in option premium. In mathematical terms, vega can be expressed as follows:

\[
Λ = \frac{\partial V}{\partial \sigma}
\]

(5.18)

The Black-Scholes model identifies vega as the following term:
\[ \Lambda = S \sqrt{t} N'(d_1) \]

5.5.2.5.5. Rho (\( \rho \))

Rho measures the change in an option's price with respect to a percentage point change in the interest rate. In mathematical terms, it is shown by the following equation:

\[ \rho = \frac{\partial V}{\partial r} \]  

(5.19)

In the Black-Scholes model, rho can be calculated by the following formula:

\[ \rho = t E e^{-rt} N(d_2) \]

5.5.2.5.6. Price sensitivity of all Greek letters

Separate calculation of Greek letters is less informative when the factors which influence the premium interact simultaneously. The simultaneous calculation of the sensitivity of option premium with respect to all Greek letters may provide comprehensive information concerning the sensitivity of option premium. The sensitivity of option price to delta, gamma, vega, rho and theta can be solved by using the Taylor expansion series (J.P. Morgan, 1996). This approach assumes that a linear relationship exists between the price of options and the factors for which the sensitivity is calculated. Vlaar (1996) suggests that linear approximation is adequate in this sensitivity analysis except in the case of the delta. Furthermore, Vlaar also mentions that the second order derivation of each risk factor can be ignored since the linear relationship is almost certain and correlation among risk factors is insignificant. Finally, we can construct the following equation:
\[ V(X, K, r, t, \sigma) = V_0(S, K, r, t, \sigma) + \frac{\partial V}{\partial S} \bigg|_{\sigma_0} (X - S) + \frac{1}{2} \frac{\partial^2 V}{\partial \sigma^2} \bigg|_{\sigma_0} (X - S)^2 + \frac{\partial^2 V}{\partial r^2} \bigg|_{\sigma_0} (r - r_0)^2 + \frac{\partial V}{\partial t} \bigg|_{\sigma_0} (t - t_0)^2 + \]

where,

- \( V \) = value of option
- \( X \) = expected price of underlying instruments for time \( t \)
- \( r \) = riskless rate of interest during the time to maturity of option
- \( t \) = time to maturity
- \( \sigma \) = standard deviation of returns on the underlying asset
- \( dV \) = delta value of option which is calculated from the partial derivatives for \( V \) with respect to \( X, r, t, \) and \( \sigma \).
- \( S \) = spot price of underlying instruments
- \( K \) = strike price

### 5.5.3. Application of VaR to options

Calculating the risk of options which are not linear instruments can be performed in many ways depending on the particular structure of options positions such as whether the option is "in the money", "at the money", or "out of the money", and the time to expiration. There are many valuation approaches which are available as discussed in this section. The most common approaches are the delta valuation method (i.e. parametric approach) and the full valuation method. The full valuation method is more appropriate to value options which contain non linear relationships between prices and risk factors. However, this study will adopt the parametric approach to calculate the value of options by considering the sensitivity of option prices with respect to the second order approximation of the risk factors. It means we assume that the change in option price is linearly related to the price of underlying assets. The main reason for using this approach
is that the full valuation method, using the sensitivity of all risk factors, requires too much data which is not always available. Additionally, banks in Indonesia are less involved in options, particularly the writing of options.

5.6. Equities

An equity position is defined as the holding of equities for trading purposes. To calculate the VaR for equity positions, we can multiply the current value (mark-to-market) of the equity position by the volatility of stock returns. The VaR can be expressed in the following equation:

\[
VaR = \text{Market value of stock} \times (1)\sigma_{R_s} 
\]

where

\[
R_s = \beta_s R_M + \alpha_s + \varepsilon
\]

and

\[
R_m \quad = \text{the return of the market index} \\
\beta_s \quad = \text{a measure of the expected change in } R_s \text{ given a change in } R_m \text{ (beta)} \\
\sigma_s \quad = \text{the expected value of a stock’s return (i.e. risk-related firm specific)} \\
\varepsilon \quad = \text{the random element of the firm’s specific return}
\]

In other words, the return of asset "s" depends on \((\beta_s R_M)\) and components of stock-specific \((\alpha_s + \varepsilon_s)\) returns.

Assume that the stock-specific return can be neutralised by diversifying the portfolio into a different number of stocks; the risk of the stock is a function of the stock index. Therefore, in mathematical terms:

\[
\sigma_{R_s} = \beta_s \cdot \sigma_{R_M} 
\]
Substituting in the VaR equation, we obtain:

\[ \text{VaR}_i = MV_i \beta_i (1) \sigma_{R_i} \]  

(5.23)

To estimate the market risk for a multi-index portfolio, the additional process of calculating correlation among indices is necessary. Similarly, for stock positions denominated in foreign currency, we need to consider foreign exchange risk.

This study excludes equity positions from empirical study, because banks in Indonesia are prohibited from taking equity trading positions. The discussion of equities in this subsection is to provide a comprehensive coverage of the theory of risk evaluation for financial instruments.

5.7. Conclusions

From what we have discussed in this chapter, we discover that most of the valuation theories are unable to accommodate credit risk simultaneously in the calculations. This finding supports the case for calculating credit risk separately from market risk.

To evaluate the value of positions, each evaluation model is designed for a particular objective, such as measuring sensitivity with respect to a certain factor, valuing positions for hedging purposes or quoting the price for arbitrage purposes. Additionally, the valuation model is normally designed for pricing and not for risk evaluation purposes. Therefore, the results are less applicable for the measurement of risk. However, we can adopt some of these theories within our risk evaluation methodology since there is no better approach - hence the use of the delta of options and the Black-Scholes model.

Finally, this study will employ the VaR approach in an empirical study of how to calculate the risk of positions in financial instruments. The examples in this chapter show the basic
format of the VaR calculations. However, adjustment may be necessary with respect to variations in financial instruments.
Chapter 6

Foreign Exchange Rate Risk Assessment Using Alternative Models: Empirical evidence

6.1. Introduction

The popularity of modelling to measure risk volatility has increased dramatically in the banking and finance industries since the inclusion of market risks (i.e. interest rate, price, and foreign exchange risk) in capital adequacy regulations (Hall, 1996; BIS, 1996; Bank of England, 1995). Most of the modelling techniques attempt to counter the methodologies adopted in those proposals.

In chapters 4 and 5, we outlined the important role that volatility plays in the assessment of the risk of banks’ portfolios. J.P. Morgan suggests to use an exponential weighted moving average with a 0.94 decay factor in estimating the volatility of returns. However, historical data of time series may show different behaviour. In other words, there is no guarantee that the exponential decay approach is fit for the time series.

The difference in the volatility behaviour is driven by the different economic processes and the speed of the distribution of news about the asset’s fundamental value. If news is spread out freely and rapidly through the media, the volatility returns will exhibit a short period interval. Considering this argument, the volatility of a particular time series will require a different model from others to generate the best estimates with the smallest errors. This study will review the various models of forecasting and identify the most appropriate one to estimate the IDR’s volatility in order to assess foreign exchange risk for Indonesian banks. This risk is important for the measurement of the adequacy of capital with respect to market risk.
To forecast volatility using historical time series, we can use either univariate (time series) or multivariate (i.e. causal relationship) models. The causal relationship method gives a better fit of future estimation since there is no changing of the behaviour of explanatory variables such as a change in economic policy (Lucas, 1976). Due to the difficulties of ensuring the stability of government policy, the univariate model is preferable. This chapter will begin with discussion of general models for risk assessment and continue with discussion on how to treat data and volatility in forecasts.

In general, univariate forecasting methodologies consist of smoothing, decomposition and causality (Makridakis, 1983, pp.17-54) models. The smoothing method adopts the principle that the current forecast is a reflection of the previous forecast and the current errors. This method includes equally-weighted moving average (EqWMA) and exponentially-weighted moving average (ExWMA). The exponential method has been used by J.P. Morgan since 1994 to provide volatility data for its clients (J.P. Morgan, 1994). The difference between the two depends on the weights. The ExWMA gives different weights to each observation while the EqWMA employs the same weights for all observations.

The decomposition method is based on the principle of breaking down a time series into each component of seasonality or trend cycle and then predicting the future from each component separately. Causality methods forecast the variation of the dependent variable based on some explanatory variables. The most widely used of the causality methods includes the autoregressive process (AR), autoregressive integrated moving average (ARIMA), autoregressive conditional heteroscedasticity (ARCH), and generalised autoregressive conditional heteroscedasticity (GARCH) - see Engle (1991), Bollerslev (1986), and Box-Jenkins (1976) for details. This chapter will provide a theoretical overview of forecasting using ExWMA (in later discussion, we shall call it EWMA), AR, ARIMA, ARCH and GARCH, and conduct an empirical study. The aims of the empirical study are to obtain evidence as to whether the J.P. Morgan decay factor (0.94) is valid for the volatility of IDR exchange rate returns, and to suggest different models which provide...
more accurate estimates. Using the foreign exchange positions of an Indonesian bank - a major forex player in the market - this study identifies the foreign exchange rate risk of the bank as assessed using the BIS standardised methodology, EWMA and GARCH. This chapter will proceed in the following way: Section 6.2 outlines the models; Section 6.3 discusses the data; Section 6.4 shows how to identify the patterns of data; Section 6.5 reviews the theories of exponential weighted moving average; Section 6.6 provides details on the theories of ARIMA and GARCH models, including empirical evidence; Section 6.7 discusses the empirical results of GARCH models; Section 6.8 discusses the testing of GARCH estimates; Section 6.9 assesses foreign exchange risk using volatility and correlation; Section 6.10 contains the conclusions of this chapter.

6.2. Models

The main objective of this section is to design new models for market risk. The discussion below is mainly based on the theories which have been discussed in Chapters 4 and 5. Adopting the definition in Chapter 4, VaR measures risk over a fixed span of time in which positions are assumed to remain fixed. This study adopts a one day time horizon to assess the VaR of foreign exchange positions. This time horizon is reasonable for measuring the risk of foreign exchange positions, but it is less appropriate for fixed income positions. The following equation is the mathematical expression of VaR for a single position:

\[ \text{VaR}_{t+1} = V_t \sigma_{t+1} \]  

(6.1)

where,

- \( \text{VaR}_{t+1} = \) value at risk
- \( V_t = \) market value of positions at time \( t \) (risk exposure)
- \( \sigma_{t+1} = \) volatility of risk factors at time \( t+1 \)

If the model above is employed within the standardised methodology of the BIS guidelines, we can derive the following conclusions:
Chapter 6 - Foreign Exchange Rate Risk Assessment Using Alternative Models: Empirical evidence

- $V$ is marked to market only for the trading book. The proposal doesn't mention how to calculate market value for fixed incomes positions or OTC derivatives.
- $\sigma$ is determined based on consensus between member countries (i.e. 8% for foreign exchange risk).
- Overall risk equals the summation of the risk of individual positions (i.e. ignoring risk correlation). This approach violates portfolio theory (see Sharp, 1970, pp. 34-44).

Detailed criticisms of the standardised method have been discussed in Hall (1994 and 1995).

This study suggests expanding the application of VaR to positions in fixed incomes and OTC derivatives. The marked-to-market values ($V$) for fixed incomes and OTC derivatives can be derived from the following models:

$$V_t = C_{t+k} \frac{1}{(1+i)^k}$$  \hspace{1cm} (6.2)

where,

$C_t =$ cash flow at time “$t$”

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

$k =$ period from the time the risk is assessed (“$t$”) to “$t+k$”

This study also suggests that the volatility of risk factors at time “$t+1$” ($\sigma_{r,k}$), such as exchange rates, stock prices, interest rates, and commodities, can be estimated using time series forecasting techniques.

Daily value at risk of the “$n$th” instrument at time “$t$” can be shown in the following equation:

$$DaR_{n,t} = V_{n,t}\sigma_{n,t+1}$$
where,

"t + 1" is the day after "t" (i.e. the day when the risk is assessed)

$\sigma_{n,t+1}$ = the daily price risk for the instrument "n"

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

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

(6.3)

where,

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

$i_r$ = the spot rate of a zero coupon bond in currency "r" for "k" periods ahead.

$k$ = the time when the cash flow is received

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

$$ \sigma_{P_k} = \sigma_{i_r} P_k $$

(6.4)

where,

$\sigma_{P_k}$ = the price volatility of a "k" period zero coupon bond

$\sigma_{i_r}$ = the daily yield volatility of a "k" period zero coupon bond in currency "r"

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

$$ DDaR_{nj} = \sqrt{\left( DaR_n^2 \right) + \left( DaR_j^2 \right) + 2* \rho_{nj} * DaR_n * DaR_j} $$

(6.5)

where,

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

---

18 Price volatility is normally used for fixed income valuations when the price of an instrument is not linearly related one to one to the yield.
Chapter 6 - Foreign Exchange Rate Risk Assessment Using Alternative Models: Empirical evidence

\[ DaR_n = \text{Daily value at risk for instrument "n"} \]

\[ DaR_j = \text{Daily value at risk for instrument "j"} \]

\[ \rho_{nj} = \text{Risk correlation between risk factors in instruments "n" and "j"} \]

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

\[
V(P,K,t,r,\sigma) = \left. \frac{\partial V}{\partial \sigma} \right| _{\sigma=\sigma_0} (K-P) + \left. \frac{1}{2} \frac{\partial^2 V}{\partial \sigma^2} \right| _{\sigma=\sigma_0} (K-P)^2 + \ldots \ldots + \left. \frac{1}{2} \frac{\partial^2 V}{\partial \sigma^2} \right| _{\sigma=\sigma_0} (\sigma-\sigma_0)^2
\]

where,

\[ V = \text{estimated value of option} \]

\[ V_0 = \text{value of options at time "i_0"} \]

The DaR of options depends on the volatility of the risk factors which can be estimated using forecasting techniques. Diversified risk in options can be solved by employing the correlation of underlying factors (i.e. \(P, K, t, r, \sigma\)). Normally we call these the “Greek letters”.

6.3. Data

This study employs daily spot exchange rate returns of 18 IDR exchange rates which are going to be used to assess foreign exchange risk for a sample bank. The time series of exchange rate returns consists of data from 2 January 1996 to 30 May 1997 or 350 observations. The length of the time series is considered long enough, particularly for EWMA. The length of the data series will not affect the results too much since the model
gives high weights to recent observations. The weights will die exponentially to zero as the observations move back to the older observations. In GARCH models, a longer time series will provide better results when these models can capture the long patterns of the time series. One of the purposes of this study is to show that GARCH models can provide more accurate IDR volatility returns than the standardised method and EWMA.

Exchange rate returns in this study are derived from the following formula:

\[ r_t = (\ln R_{t+1} - \ln R_t) \times 100\% \]  \hspace{1cm} (6.7)

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 quote prices of Bank Negara Indonesia (a commercial bank). The ownership of this bank is split between government and private owners (i.e. public shareholders). Therefore, we believe that the exchange rate policy of this bank is likely to be independent from involvement of the owners. The exchange rate and exchange rate returns are shown in the following graphs:
Graph 6.1
Graphs of IDR Exchange Rates and Exchange Rate Returns
(From 1 January 1996 - 30 May 1997)

Original series

ATS

Delta log normal

Original series

AUD

Delta log normal

BEF

BND

CAD

CHF
Graph 6.1 (continued)

<table>
<thead>
<tr>
<th>Original series</th>
<th>Delta log normal</th>
<th>Original series</th>
<th>Delta log normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>JPY</td>
<td></td>
<td>MYR</td>
<td></td>
</tr>
<tr>
<td>NLG</td>
<td></td>
<td>NZD</td>
<td></td>
</tr>
<tr>
<td>SEK</td>
<td></td>
<td>USD</td>
<td></td>
</tr>
</tbody>
</table>

VI-10
As the last graph shows, the IDR is a managed float against the USD as the trend line increases at the same sequence. It is in line with the government's announcement that Indonesia adopts a managed float for its foreign exchange rate policy.

To assess foreign exchange risk, this study will employ the net foreign exchange positions of a state bank in Indonesia. However, regulations in Indonesia do not allow the name of the bank to be revealed. The foreign exchange exposure of the bank is a consolidated position on 30 May 1997. The internal management of the sample bank has employed several guidelines to ensure that the foreign exchange trading exposure is within a level at which the management of the bank thinks the bank is secure. These restrictions include the setting of a maximum overnight open position of foreign exchange trading of US$7,500 for each dealing room. However, most forex dealers square their positions at the end of the day. Therefore, the forex position from the banking book dominates the consolidated position. The positions in foreign exchange will be used to assess foreign exchange risk using the standardised method and GARCH. The foreign exchange position of the sample bank and the methodology for calculating the capital requirement using the standardised method are given in Table 6.1 below.
Table 6.1
Foreign Exchange Risk Using the BIS Standardised Method

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

Foreign exchange risk 8% from 365,290,374

6.4. Identification of the patterns of data

Forecasting in mean-variance analysis requires certain conditions to get the best results. The most important requirement is the stationarity of the data. Data is stationary when the process of generating this data is in equilibrium around a constant value and the variances around the mean remain constant over time. A non-stationary process of time series occurs when trend or seasonal effects, or combinations of them, generate the process of the series. Some modelling techniques assume that means and variances are constant over time. If a time series is generated from a non-stationary process, this process is redundant with the assumption of constant means and variances. Therefore, the mean-variance approach will not give the best results. The EWMA will be more appropriate for non-
stationary time series. However, the mean variance analysis may produce better estimates since the model considers the heteroscedastic variances. The following discussion covers the theories of stationarity and whitenoise tests.

6.4.1 Sample autocorrelation function (ACF)

In time series data, the probability of an observation falling by a certain value is assumed to be drawn from a random process (i.e. the series was generated by a stochastic process). However, the stochastic process of time series data may follow a certain pattern such as horizontal, seasonal, cyclical, trend, or combinations of these patterns.

An autocorrelation function (ACF), which measures the relationship between two observations within a time series, is the standard method to examine the patterns of data. If the ACFs are significantly different from zero, the data is not random (non-stationary). In other words, past values may influence current values in the time series. If the process of the data is non-stationary (i.e. the data is time variant), the estimation of the future with fixed coefficients of parameters is misleading (Pindyck, 1991, p.444). Another indication of a stationary process is when the ACF drops to zero immediately or exponentially (see Enders, 1995, p.85). If a time series is not generated from a stationary process, it will be necessary to transform the series into a stationary generated process before we employ these series in models.

The ACF at lag “k”, (we normally use symbol \( p_k \)), can be derived from the relative value of covariance between two observations over the product of the two standard deviations. To keep it simple, the discussion below begins with the correlation in a bivariate time series model even though the application to univariate time series is the same. In mathematical terms we can express the correlation of the bivariate time series data (X and Y) in the following equation:
\[ r_{XY} = \frac{\text{Cov}_{XY}}{S_X S_Y} \]  

(6.8)

where,
\[ \text{Cov}_{XY} = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y}) \quad \text{and} \quad \]
\[ S_X = \frac{1}{n-1} \sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2} \]
\[ S_Y = \frac{1}{n-1} \sqrt{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \]

where,
- \( \text{Cov}_{XY} \) = covariance between series X and series Y
- \( S_X \) = standard deviation of series X
- \( S_Y \) = standard deviation of series Y

The autocorrelation in univariate time series data is the correlation between an observation at time “t” and an observation at time “\( t-k \)”, we can call it an autocorrelation with lag “\( k \)”. Given a time series \( (X_1, X_2, \ldots, X_n) \), the autocorrelation at lag “\( k \)” can be expressed in the following equation:

\[ \text{Autocorrelation (lag } k \text{)} = p_k = \frac{\sum_{t=k+1}^{n} (X_t - \bar{X})(X_{t-k} - \bar{X})}{\left( \sqrt{\sum_{t=k+1}^{n} (X_t - \bar{X})^2} \right) \left( \sqrt{\sum_{t=k}^{n} (X_t - \bar{X})^2} \right)} \]  

(6.9)

where,
\[ \bar{X} = \frac{1}{n-k} \sum_{i=k+1}^{n} X_i \]
\[ k = 1, 2, 3, \ldots, \]

If the series are identified as invariant with respect to time (i.e. stationary), these series will satisfy the following conditions:
(1) The series have a constant mean or the mean is invariant of time.
(2) The series have a constant variance. This condition implies that the variances will be the same whatever the "n" which is calculated in the following: \[ \sum_{t=1}^{n} (X_t - \bar{X})^2 = \sigma^2 \]
(3) The covariance \( \gamma_k = (X_t - \bar{X})(X_{t-k} - \bar{X}) \) is always the same for the same "k".

Finally, we can rearrange equation in point 3 into the following:

\[
\gamma_k = \sum_{t=k+1}^{n} (X_t - \bar{X})(X_{t-k} - \bar{X}) \\
p_k = \frac{\sum_{t=k+1}^{n} (X_t - \bar{X})(X_{t-k} - \bar{X})}{\sum_{t=1}^{n} (X_t - \bar{X})^2}
\]

where
\[
\sum_{t=1}^{n} (X_t - \bar{X})^2 = \gamma_0
\]

Therefore, \( p_k = \frac{\gamma_k}{\gamma_0} \) \hspace{1cm} (6.10)

6.4.2. Test of a whitenoise process

Assuming the series is \( y_1, y_2, y_3, \ldots, y_t \) and the autoregressive process is given by the following equation \( y_t = a y_{t-1} + \epsilon_t \), the series is generated from a whitenoise process if \(-1 < a < 1\) (Enders, 1995, p.215). Another indication of the whitenoise process is when the ACF drops to zero in the first of several lags. To test whether the \( p_k \) is significantly different from zero, we assume that \( y_t \) is independent of \( y_{t-1} \) (or \( a = 0 \)) and \( \epsilon \) is white noise; then the autocorrelation of \( \rho_0 = 1 \) and \( \rho_k = 0 \) for \( k > 0 \). By using a sample, we can test whether \( \rho_k = 0 \) for \( k > 0 \) (Bartlett, 1946). According to Bartlett, sample autocorrelation coefficients are approximately normally distributed with zero mean and variance \( 1/n \).

Given the time series data of daily exchange rate returns for the USD/IDR from 2 January 1996 to 30 May 1997 (i.e. \( T=350 \)), the variance is \( 1/350 \) and standard deviation is
\[
\frac{1}{\sqrt{350}} = 0.053452.\] Assuming we use a 95% confidence interval in a standard normal distribution, any \( p_k \) will lie within the following range - 
\[0.104765 \leq p_k \leq 0.104917\] 
\((1.96 \times 0.053452 = 0.104917)\). We will accept the hypothesis that the true value of \( p_k \) is zero if the \( p_k \) falls inside the interval value. From the correlogram (Table 6.2), we can see that the values of \( p_k \) for \( k>1 \) fall inside the interval; thus we accept the hypothesis that the true value of \( p_k \) is close to zero for \( k>1 \). However, for \( k=1 \), the value of \( p_k \) falls outside the interval.

The USD/IDR correlogram shows that the ACF drops to zero after the third lag so we suspect that the time series of the USD/IDR is white noise. The correlogram test for other currencies also shows that the ACF drops immediately to zero \(^{19}\) and all the time series of foreign exchange rate returns on IDR may be stationary at the series level.

This study also tests the significance of ACF using Q Statistics developed by Box and Pierce (Box and Pierce, 1970). This method employs the hypothesis that the coefficient of ACF equals zero \(( H_0: \rho_k = 0)\).

Consider the following equation:

\[
Q = n \sum_{k=1}^{m} \rho_k^2 
\]

(6.11)

where,

\( n = \) sample size

\( m = \) lag length

\(^{19}\) For the purposes of this discussion, we use only the USD/IDR series. Modelling for other currencies adopts the same methodologies as those used for USD/IDR.
According to Box and Pierce, the distribution of $Q$ follows the chi-square distribution with $m$ degrees of freedom. If the value of $Q$ exceeds the critical $Q$ value from the chi-square table at the chosen level of significance, we reject the hypothesis that the values of all $p_k$ are zero.

However, this test is more appropriate for large samples. Ljung-Box (1978) claim that their model can produce better results than those produced by the use of the Q-statistic. Ljung-Box suggest using the following formula:

$$LB = n(n+2)\sum_{k=1}^{m} \left( \frac{\rho_k^2}{n-k} \right)$$

(6.12)

Theoretically, the value of LB also follows the chi-square distribution with $m$ degrees of freedom. Table 6.2 shows the results of the correlogram, ACF, PACF, Q-statistic calculated using Ljung-Box, and Box-Pierce on USD/IDR exchange rate returns.
# Table 6.2

Stationary Test of USD/IDR at Original Series Level

<table>
<thead>
<tr>
<th>Lags</th>
<th>ACF</th>
<th>PACF</th>
<th>ACF</th>
<th>PACF</th>
<th>LB</th>
<th>BP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>****</td>
<td>****</td>
<td>-0.394</td>
<td>-0.394</td>
<td>57.59</td>
<td>57.13</td>
</tr>
<tr>
<td>2</td>
<td>*</td>
<td>*</td>
<td>0.012</td>
<td>-0.170</td>
<td>57.65</td>
<td>57.18</td>
</tr>
<tr>
<td>3</td>
<td>*</td>
<td>*</td>
<td>0.041</td>
<td>-0.026</td>
<td>58.27</td>
<td>57.80</td>
</tr>
<tr>
<td>4</td>
<td>*</td>
<td>*</td>
<td>-0.043</td>
<td>-0.040</td>
<td>58.96</td>
<td>58.48</td>
</tr>
<tr>
<td>5</td>
<td>*</td>
<td>*</td>
<td>0.000</td>
<td>-0.034</td>
<td>58.96</td>
<td>58.48</td>
</tr>
<tr>
<td>6</td>
<td>*</td>
<td>*</td>
<td>-0.001</td>
<td>-0.024</td>
<td>58.96</td>
<td>58.48</td>
</tr>
<tr>
<td>7</td>
<td>*</td>
<td>*</td>
<td>0.037</td>
<td>0.034</td>
<td>59.46</td>
<td>59.25</td>
</tr>
<tr>
<td>8</td>
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<td>*</td>
<td>-0.027</td>
<td>0.003</td>
<td>59.73</td>
<td>59.25</td>
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<tr>
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<td>*</td>
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<td>0.067</td>
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</tr>
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<td>*</td>
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<tr>
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<td>*</td>
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<tr>
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<td>-0.035</td>
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<tr>
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<td>*</td>
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<td>0.027</td>
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</tr>
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<tr>
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<td>*</td>
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<td>0.012</td>
<td>63.96</td>
<td>63.45</td>
</tr>
<tr>
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<td>*</td>
<td>0.001</td>
<td>0.019</td>
<td>63.96</td>
<td>63.45</td>
</tr>
<tr>
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<td>*</td>
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<td>0.004</td>
<td>64.00</td>
<td>63.48</td>
</tr>
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<td>*</td>
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<td>-0.056</td>
<td>64.79</td>
<td>64.26</td>
</tr>
<tr>
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<td>*</td>
<td>0.040</td>
<td>-0.002</td>
<td>65.38</td>
<td>64.85</td>
</tr>
</tbody>
</table>

Note: LB = Ljung Box Q Statistic
BP = Box-Pierce Q Statistic
Single * indicates that the ACF/PACF falls below significant level.
More than one * indicates that the ACF/PACF falls above significant level.
This test uses a 5% confidence level.

### 6.4.3. Partial autocorrelation function (PACF)
Partial autocorrelation is the degree of association between observations \( Y_t \) and \( Y_{t-k} \) when the effect of other time lags 1, 2, 3, ... up to \( k - 1 \) are partialled out. This partial autocorrelation can also be defined as the last autoregressive coefficient of an autoregressive with order \( k - 1 \) or AR(\( k - 1 \)) model. The purpose of defining the PACF is to identify an appropriate ARMA process in forecasting. The following equations show how to derive an AR(1), AR(2), AR(3), ... AR(\( m - 1 \)), and an AR(\( m \)).

\[
Y_t = \phi_1 Y_{t-1} + e_t \quad (6.13)
\]
\[
Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + e_t \quad (6.14)
\]
\[
Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + e_t \quad (6.15)
\]
\[
Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + \ldots + \phi_{m-1} Y_{t-(m+1)} + e_t \quad (6.16)
\]
\[
Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + \ldots + \phi_{m-1} Y_{t-(m+1)} + \phi_m Y_{t-m} + e_t \quad (6.17)
\]

Theoretically, we can solve \( \hat{\phi}_1, \hat{\phi}_2, \hat{\phi}_3, \ldots, \hat{\phi}_{m-1}, \hat{\phi}_m \) using these equations. However, the computation will be time consuming. To solve \( \hat{\phi}_1 \), we can multiply the equation of AR(1) by \( Y_{t-1} \) and we obtain the following equation:

\[
Y_t Y_{t-1} = \phi_1 Y_{t-1} Y_{t-1} + Y_{t-1} e_t \quad (6.18)
\]

Taking the expected value of the equation above, we get the following equation:

\[
E(Y_t Y_{t-1}) = E(\phi_1 Y_{t-1} Y_{t-1}) + E(Y_{t-1} e_t)
\]

Since \( E(Y_t Y_{t-1}) = \gamma_1 \), \( E(Y_{t-1} Y_{t-1}) = \gamma_0 \) and \( E(Y_{t-1} e_t) \) is assumed to be zero, therefore:

\[
\gamma_1 = \phi_1 \gamma_0
\]
Rearranging the equation above we can solve PACF with order 1 ($\rho_1$):

\[
\frac{\gamma_1}{\gamma_0} = \phi_1
\]

\[
\rho_1 = \phi_1
\]  

(6.19)

The same methodology applies for solving other $\phi_k$ by employing the following procedures: (1) multiplying the equation by $Y_{i-k}$; (2) taking expected values of the equations; (3) dividing the expected values by $\gamma_0$ will produce a set of simultaneous equations (i.e. Yule-Walker equations) which can be solved for $\phi_k$.

The next concern is how the value of $\phi_k$ can be used to identify the ARMA model. If the value of $\phi_k$ is significantly different from zero, the time series is identified as an AR($k$) process. It is possible that more than one AR($k$) is significant. However, if the series was generated from the MA process instead of AR, then the PACF will not indicate the order of the MA process. A general rule says that the MA process can be identified when the PACF do not exhibit a drop to random values after "k" lags but instead decline to zero exponentially (see Appendix 6.1 for details.). The stationary test on the USD/IDR series shows that the PACF drops to zero at the third lag. This may indicate that the series is not generated from an MA process.

### 6.4.4. Unit root test

Even though we have already examined a sample ACF, there is still an argument that, sometimes, a sample ACF (i.e. correlogram) fails to detect stationary process. This technique makes it hard to distinguish between unit roots and near unit roots because they have the same shape as in ACF. The next step in this discussion is to identify whether a series is generated from unit roots and to conclude whether the process of the series is stationary.
If the ACF drops slowly (not in a multiplicative process), a time series may contain a characteristic of a unit root process and a trend stationary process. In the previous section, we tested ACF under the null-hypothesis that $\rho_k = 0$, and the result provides information on whether the ACF is significantly different from zero. However, it is unclear whether it is a unit root process. In the unit root test, we will employ the hypothesis that the series is non-stationary by employing $H_0: (\rho = 1)$ in the equation 6.20 below. Recall the following equation:

$$ y_t = a_1 y_{t-1} + \varepsilon $$

The unit root test will determine whether the coefficient of $a_1$ equals 1. This section will discuss the methodology of the unit root test and in this connection we will adopt the Dickey-Fuller test (Dickey and Fuller, 1979). A time series is probably generated from a random walk with drift as the effects of a temporary shock (i.e. this drift is reflected in a constant term) and trend. Let us examine the following equation:

$$ y_t = \alpha + \beta t + \rho y_{t-1} + \varepsilon_t $$

where,

$y_t$ = the observation at time “t”
$\alpha$ = the constant term
$\varepsilon_t$ = the error term at time “t”
$t$ = the times
$\beta$ = the coefficient of the trend parameter

Detail on the mathematical background may be found in Appendix 6.2.
The equation above suggests that an observation in a time series is a function of a constant, time, previous observations and errors. Theoretically, a time series grows because of two factors:

1. A time series grows as a result of a trend reflected by the coefficient of \( t \). However, this trend effect can be removed by detrending the series (i.e. make coefficient \( \rho < 1 \)). The most common approach is by adding \( \Delta y_t \) to the both sides of the equation.

2. The other source of the growth is random walk with a positive drift (i.e. \( \alpha > 0, \beta = 0, \) and \( \rho = 1 \)). If this condition exists, detrending will not help and the regression will lead to spurious regression (Granger and Newbold, 1974).

To test whether \( \rho = 1 \), we can adopt the Dickey-Fuller distribution estimator of \( \rho \).

This test employs the following procedure:

1. Run unrestricted OLS regression of the following equation:
   \[
   Y_t - Y_{t-1} = \alpha + \beta t + (\rho - 1)Y_{t-1} + \lambda_t \Delta Y_{t-1}
   \]

2. Run restricted regression of the following equation:
   \[
   Y_t = \alpha + \lambda_t \Delta Y_{t-1}
   \]

3. Calculate the standard F ratio to test whether the restrictions of \( \beta = 0, \) and \( \rho = 1 \) hold.

The F ratio is calculated in the following formula:

\[
F = \frac{(N - k)(SSER - SSE_{UR})}{q(SSE_{UR})}
\]

where,

- \( SSE_R \) = the sum square errors of restricted regression
- \( SSE_{UR} \) = the sum square errors of unrestricted regression
- \( N \) = the number of observations
- \( k \) = the number of estimated parameters in the unrestricted regression
- \( q \) = the number of parameter restrictions

A unit root sequence exists when \( \rho - 1 = 0 \) or \( \rho = 1 \) and a deterministic trend exists when \( \beta \) is significantly different from zero. Using the Dickey-Fuller distribution table, we can reject or fail to reject (accept) the hypothesis that \( \beta = 0, \) and \( \rho = 1 \). If the critical value
on the table with a certain confidence interval is larger than the F ratio, we fail to reject the hypothesis.

This study runs the Dickey-Fuller test for exchange rate returns of IDR and the results are shown in Appendix 6.3. Working from these results, we reject the hypothesis that the time series of IDR exchange rate returns are generated from a random walk with a 5% confidence level.

6.4.5. Identification results

This study employs daily data of exchange rate returns on IDR against 18 currencies from January 1996 to May 1997. The 18 currencies are selected on the basis of the foreign exchange risk exposure of a state bank in Indonesia; we will use its foreign exchange positions as samples to assess foreign exchange risk. By employing the techniques discussed in the previous sections, the results of Ljung-Box and Box-Pierce stationary tests are shown in Appendix 6.4. This table shows that all series are stationary at a 5% confidence level. Stationarity at the level of the time series is achieved because the series in this study is derived from the log normal of exchange rate returns. Based on the Dickey-Fuller test, the results show the rejection of the hypothesis that the time series are generated from a random walk ($\rho$ is significantly different from 1 even at a 1% confidence level). The Dickey-Fuller test supports the conclusion in the Ljung Box and Box-Pierce tests that these series are stationary at level of the series (see Appendix 6.3). Finally we conclude that these series are eligible for use in forecasting.

6.5. 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.
6.5.1. 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 \( \hat{F}_{t+1} \) is a function of the previous forecast \( \hat{F}_{t} \) 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:

\[
\hat{F}_{t+1} = \alpha \hat{F}_{t} + (1- \alpha) X_t
\]  

(6.21)

where,

\( \alpha \) = the decay factor with a constraint of \( 0 < \alpha < 1 \),

\( \hat{F}_{t+1} \) = the forecast of variance at time \( t+1 \)

\( X_t \) = the observation (i.e. sample variance) at time \( t \)
We can rearrange equation 6.21 by replacing the definition of $F_t$ and substituting for 
$(1-\alpha) = \rho$ in the following equation:

$$F_{t+1} = \alpha(F_{t-1} + \rho X_{t-1}) + \rho X_t$$

$$= \alpha^2 F_{t-1} + \alpha \rho X_{t-1} + \rho X_t$$

$$= \alpha^2 (\alpha F_{t-2} + \rho X_{t-2} + \alpha \rho X_{t-1} + \rho X_t$$

$$= \alpha^3 F_{t-2} + \alpha^2 \rho X_{t-2} + \alpha \rho X_{t-1} + \rho X_t$$

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

$$F_{t+1} = \alpha^q \rho X_{t-q} + \alpha^{q-1} \rho X_{t-(q-1)} + ....... \alpha^3 \rho X_{t-3} + \alpha^2 \rho X_{t-2} + \alpha \rho X_{t-1} + \rho X_t$$

$$F_{t+1} = \rho \sum_{i=0}^{q} \alpha^i X_{t-i}$$

Additionally, model 2 can be applied:

Model 2:

$$F_{t+1} = \alpha X_t + (1-\alpha) F_{t-1}$$

The value of $\alpha$ plays an important role in EWMA. If the value of $\alpha$ equals a figure 
which is close to 1 (see equation 6.21), this forecast will adopt a small adjustment for the 
errors in the previous forecast. On the other hand, if the value of $\alpha$ is close to 0, the 
model gives substantial adjustment of the previous errors. Without any rule to decide the 
value of $\alpha$, we can select the value of $\alpha$ to get the intended results of forecasting.

Indicators to decide the value of $\alpha$ 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 $\alpha$. Using time series data, the best value of $\alpha$ 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 \( \alpha \) is close to 1, the initial value plays a crucial part in forecasting. However, since the time "\( T \)" is large enough and the \( \alpha \) 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.

To test the results, this study will employ Theil’s U Statistic since this method has been used widely to measure the accuracy of forecasting (Makridakis, 1983, pp.43-52 and Trigg, 1964). In mathematical terms, Theil’s U statistic can be shown in the following:

\[
U = \sqrt{\frac{\sum_{i=1}^{n-1} (FPE_{i+1} - APE_{i+1})^2}{\sum_{i=1}^{n-1} (n - 1)}}
\]

where,

\[
FPE_{i+1} = \frac{F_{i+1} - X_i}{X_i}
\]

The forecast percentage errors (FPE) represent the forecast relative change

\[
APE_{i+1} = \frac{X_{i+1} - X_i}{X_i}
\]

The actual percentage errors (APE) represent the actual relative change

We can simplify equation 6.23 into the following:
\[ U = \sqrt{\frac{\sum_{i=1}^{n} \left( \frac{F_{i+1} - X_{i+1}}{X_i} \right)^2}{\sum_{i=1}^{n} \left( \frac{X_{i+1} - X_i}{X_i} \right)^2}} \]

The lower the Theil's U statistic, the better the fit in our forecast.

**6.5.2. 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 \( \lambda_i \) represents the optimal decay factor for instrument \( i \), \( N(i = 1, 2, \ldots, 3) \) stands for the number of time series included in forecasting, and \( \tau_i \) 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 \( \tau_i \) using the following equation:
  \[ \Pi = \sum_{i=1}^{N} \tau_i \]
- define the relative error using the following equation:
  \[ \theta_i = \frac{\tau_i}{\sum_{i=1}^{N} \tau_i} \]
- define the weight using the following equation:
  \[ \phi_i = \frac{\theta_i^{-1}}{\sum_{i=1}^{N} \theta_i^{-1}} \]
where \( \sum_{i=1}^{N} \phi_i = 1 \)

- the optimal decay factor, \( \hat{\lambda} \) is defined in as the following equation:

\[
\bar{\lambda} = \sum_{i=1}^{N} \phi_i \hat{\lambda}_i
\]

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.

If 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.

**6.5.3. Empirical results of forecasting IDR using EWMA**

By employing RMSE, the decay factors (DFs) of IDR exchange rate returns are shown in the following Table:
Table 6.3

Decay Factors (α) of IDR Exchange Rate Returns

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

The coefficients of α 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 - see Section 6.7 - suggest that this argument is invalid for
IDR exchange rate returns. Table 6.4 shows the DDaR of foreign exchange position of the sample bank calculated using EWMA with original and J.P. Morgan's decay factors.

<table>
<thead>
<tr>
<th>Currency</th>
<th>Net Position</th>
<th>Volatility(%) using original DF</th>
<th>DaR using original DF</th>
<th>Volatility (%) using a 0.94 DF</th>
<th>DaR using a 0.94 DF</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATS</td>
<td>1,236,857.82</td>
<td>-1.11</td>
<td>(13,773.95)</td>
<td>-1.04</td>
<td>(12,903.44)</td>
</tr>
<tr>
<td>AUD</td>
<td>6,107,816.04</td>
<td>0.85</td>
<td>(52,185.92)</td>
<td>0.61</td>
<td>(37,539.12)</td>
</tr>
<tr>
<td>BEF</td>
<td>488.25</td>
<td>0.12</td>
<td>(618.50)</td>
<td>0.75</td>
<td>(718.25)</td>
</tr>
<tr>
<td>BND</td>
<td>23,934.40</td>
<td>0.92</td>
<td>(221.34)</td>
<td>-0.83</td>
<td>(197.47)</td>
</tr>
<tr>
<td>CAD</td>
<td>334,552.68</td>
<td>-1.34</td>
<td>(4,477.02)</td>
<td>-1.39</td>
<td>(4,041.19)</td>
</tr>
<tr>
<td>CHF</td>
<td>1,532,203.80</td>
<td>-1.37</td>
<td>(20,943.65)</td>
<td>-1.21</td>
<td>(18,535.68)</td>
</tr>
<tr>
<td>DEM</td>
<td>6,422,919.14</td>
<td>-1.13</td>
<td>(72,824.09)</td>
<td>-0.95</td>
<td>(61,303.30)</td>
</tr>
<tr>
<td>DKK</td>
<td>425,981.25</td>
<td>-1.21</td>
<td>(5,158.97)</td>
<td>-1.15</td>
<td>(4,904.38)</td>
</tr>
<tr>
<td>FFR</td>
<td>1,799,277.12</td>
<td>-1.05</td>
<td>(18,831.83)</td>
<td>-0.92</td>
<td>(16,534.42)</td>
</tr>
<tr>
<td>GBP</td>
<td>34,886,947.65</td>
<td>-0.94</td>
<td>(327,615.84)</td>
<td>-0.88</td>
<td>(308,701.69)</td>
</tr>
<tr>
<td>HKD</td>
<td>9,021,070.80</td>
<td>0.52</td>
<td>(46,772.53)</td>
<td>-0.72</td>
<td>(65,239.71)</td>
</tr>
<tr>
<td>ITL</td>
<td>77,882,972.44</td>
<td>-0.91</td>
<td>(708,784.39)</td>
<td>-0.97</td>
<td>(753,722.13)</td>
</tr>
<tr>
<td>JPY</td>
<td>3,790,421,766.15</td>
<td>-1.91</td>
<td>(72,470,620.58)</td>
<td>-1.90</td>
<td>(72,126,065.90)</td>
</tr>
<tr>
<td>MYR</td>
<td>14,996,934.42</td>
<td>0.43</td>
<td>(64,653.94)</td>
<td>-0.37</td>
<td>(55,741.74)</td>
</tr>
<tr>
<td>NLC</td>
<td>1,219,865.56</td>
<td>-1.20</td>
<td>(14,618.11)</td>
<td>-0.98</td>
<td>(11,966.32)</td>
</tr>
<tr>
<td>NZD</td>
<td>240,219.00</td>
<td>-0.69</td>
<td>(1,658.38)</td>
<td>-0.68</td>
<td>(1,625.25)</td>
</tr>
<tr>
<td>SEK</td>
<td>320,557.77</td>
<td>-1.09</td>
<td>(3,496.05)</td>
<td>-1.03</td>
<td>(3,315.73)</td>
</tr>
<tr>
<td>USD</td>
<td>643,608,560.00</td>
<td>-0.10</td>
<td>(627,846.30)</td>
<td>-0.13</td>
<td>(826,493.34)</td>
</tr>
</tbody>
</table>

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). A plot of actual values and estimates is shown in Appendices 6.10 and 6.11.

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 white noise, and, therefore, that the GARCH model provides more accurate estimates.
6.6. Theory of the ARIMA and GARCH models

This section discusses the theory of univariate time series models as the basis of model selection procedures to decide the best models for the empirical work. The previous section (i.e. identification of patterns) notes that the mean variance analysis assumes that the means and variances are constant over time. This assumption is in line with the true process since the time series data is generated from the stationary process. The previous chapter discussed the theory and the testing of the stationarity of the data. The next step in this section is to discuss the models of mean process (ARIMA) and conditional heteroscedasticity of variances (GARCH).

6.6.1 Models of mean processes

6.6.1.1. Autoregressive (AR) models

The mean process of time series may follow an autoregressive process with certain orders. Assuming that the time series data is \( y_1, y_2, y_3, \ldots, y_T \), an autoregressive process with order \( p \) can be shown in the following equation:

\[
y_t = u + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + e_t
\]  

(6.24)

where,

- \( u \) = the constant term
- \( \phi_j \) = the \( j^{th} \) autoregressive parameter
- \( e_t \) = the error term at time “\( t \)”

This model assumes that \( e_t \) is white-noise with variance \( \sigma^2 \), and is independent from any \( y \). Using backward operators, we can rearrange equation (6.24) above into the following equation:
\[ y_t - \phi_1 y_{t-1} - \phi_2 y_{t-2} - \cdots - \phi_p y_{t-p} = u + e_t \]

\[ (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p) y_t = u + e_t \]

The parameters of an autoregressive process can be solved by employing the Yule-Walker equation. If we recall the methodology to identify PACF in section 6.4.3, then using the Yule-Walker equation we obtain:

\[ \rho_1 = \phi_1 + \phi_2 \rho_2 + \cdots + \phi_p \rho_{p-1} \]

\[ \rho_2 = \phi_1 \rho_1 + \phi_2 + \cdots + \phi_p \rho_{p-2} \]

\[ \vdots \]

\[ \rho_p = \phi_1 \rho_{p-1} + \phi_2 \rho_{p-2} + \cdots + \phi_p \]

where, \( \rho_1, \rho_2, \ldots, \rho_p \) are the theoretical autocorrelations for lags 1, 2, \ldots, \( p \) and \( \phi_1, \phi_2, \ldots, \phi_p \) are the parameters of the autoregressive coefficients. Since we know the value of \( p \) from sample autocorrelation, we can calculate the value of \( \phi \) (see Appendix 6.6).

6.6.1.2. Moving average (MA) models.

In an AR process, we assume that there is no relationship between the disturbance terms and the dependent variable. However, some previous studies have found that the dependent variable \( (y_t) \) is not always independent from the disturbance, \( e \). To treat this behaviour, we can employ MA models. The MA process with \( q \) orders is shown in the following equation:
\[ y_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_3 e_{t-3} + \ldots + \theta_q e_{t-q} \]  
(6.25)

The ACF and PACF of disturbance can be applied to test whether the MA process is significant (see Appendix 6.1). Appendix 6.7 provides the mathematical background on how to solve for the variances and covariances of the MA process, and calculate the parameters of the MA process.

6.6.1.3. Autoregressive moving average (ARMA) models

It is also possible that a time series is generated from a combination of an AR and MA models (Box-Jenkins, 1976). Assuming the time series data is an integrated time series, Box-Jenkins identify this model as an autoregressive integrated moving average (ARIMA) model. The following discussion contains the mathematical background to this model.

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

\[ y_t = \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + e_t + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q} \]  
(6.26)

The parameters of ARIMA models can be solved using the same approach as those in AR and MA processes (see Appendices 6.6, 6.7 and 6.8).

6.6.2. Generalised autoregressive conditional heteroscedasticity (GARCH)

Many authors propose different models to estimate the volatility of asset returns. Lawrence and Robinson (1995) suggest that the GARCH model is better than EWMA because GARCH can remove the autocorrelation of conditional volatility and therefore represents a satisfactory model of a data generating process. West and Cho (1995) found that EWMA can provide similar results to GARCH for short time horizons. JP Morgan
(1994) also found that EWMA with a 0.94 decay factor and GARCH (1,1) can give similar results of volatility in GBP/USD returns.

The accuracy of a model depends on many aspects such as the data, models, and accuracy assessment criteria. In other words, a good model does not always give the best estimates in all circumstances. To provide a clear picture of the volatility of IDR exchange rate returns, this study also employs GARCH in the empirical study.

The aim of this chapter is to select the best estimation model to calculate the volatility and correlation of IDR exchange rate returns. The results of the exchange rate volatility will be employed to assess the foreign exchange risk of a sample bank in Indonesia.

In forecasting, we normally assume that the variance of the disturbance term ($\sigma^2$) is constant over time "t". However, the actual volatility of a time series is not always constant. Engle (1982) introduced a forecasting method allowing the variances to 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 or a combination of AR and MA (i.e. ARMA). It is also possible when the series is integrated either at the level of the series 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 "$y_t$" at time "t" using ARMA(1,1), we can use the following equation:

$$y_t = \alpha y_{t-1} + \varepsilon_t + \beta \varepsilon_{t-1}$$  \hspace{1cm} (6.27)

where,

$y_t$ = the exchange rate return at time "t"
Chapter 6 - Foreign Exchange Rate Risk Assessment Using Alternative Models: Empirical evidence

\( a_1 \) = the slope

\( \epsilon_t \) = the residual

\( \beta \) = the coefficient of an MA process

Appendix 6.8 shows the mathematical derivation for solving the parameters.

To forecast the variance at time “\( t+1 \)” (\( \epsilon_{t+1}^2 \)) we can employ the following method:

\[
\text{Var} (y_{t+1} | y_t) = E_t [(y_{t+1} - \beta \epsilon_{t-1} - a_1 y_t)^2] \\
= E_t \epsilon_{t+1}^2 
\]

(6.28)

The ARMA process assumes that the variance is constant over time. In mathematical terms:

\[
E_t \epsilon_{t+1}^2 = E_t \epsilon_t^2 = E_t \epsilon_{t-1}^2 = \ldots \ldots = E_t \epsilon_{t-p}^2 = \sigma^2
\]

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

If we assume that the variance is conditional on the past variances, or the variance is not constant, then:

\[
\hat{\epsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\epsilon}_{t-1}^2 + \alpha_2 \hat{\epsilon}_{t-2}^2 + \ldots \ldots + \alpha_q \hat{\epsilon}_{t-q}^2 + \nu_t 
\]

(6.29)

where, \( \nu_t \) is a white-noise process (i.e. zero mean, \( \nu_t \nu_{t} (\sigma_\nu^2) = 1 \) and \( \nu_t \nu_{t-1} = 0 \))

Engle (1982) employs the multiplication form of conditional heteroscedasticity with order 1 as shown in the following:
\[ 
\varepsilon_t = \nu_t \sqrt{\alpha_0 + \alpha_1 \varepsilon_{t-1}^2} \quad (6.30) 
\]

where,

\( \nu_t \) is white noise process.

Other constraints are required for equation 6.30, such as \( \alpha_0 \) and \( \alpha_1 \) being constant, \( \alpha_0 > 0 \) and \( 0 < \alpha_1 < 1 \), and \( \nu_t \varepsilon_{t-1} = 0 \) in order to maintain the stability of the autoregressive process.

Since the unconditional autoregressive models assume that \( E\nu_t = 0 \), the unconditional mean of \( \varepsilon_t \) will be zero. The white noise process of \( \nu_t \) implies that \( \nu_t \nu_{t-1} = 0 \). From this assumption, we can also draw the conclusion that \( E\varepsilon_t \varepsilon_{t-1} = 0 \) since \( i \neq 0 \).

The discussion below tries to examine the unconditional variance of \( \varepsilon_t \). From equation 6.30, we can derive the \( E\varepsilon_t^2 \) as shown in the following equation:

\[
E\varepsilon_t^2 = E[\nu_t^2 (\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)] \\
= E\nu_t^2 E(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)
\]

If we now recall the assumptions of the white noise process of \( \nu_t \) that \( \nu_t \nu_t (\sigma^2_\nu) = 1 \) and of unconditional variance when \( E\varepsilon_t^2 = E\varepsilon_{t-1}^2 = E\varepsilon_{t-2}^2 = \ldots = E\varepsilon_{t-i}^2 \), we see that the unconditional variance can be solved in the following equations:

\[
E\varepsilon_t^2 = E\alpha_0 + E\alpha_1 \varepsilon_{t-1}^2 \\
E\varepsilon_t^2 - E\alpha_1 \varepsilon_{t-1}^2 = E\alpha_0 \\
E\varepsilon_t^2 (1 - \alpha_1) = E\alpha_0 \\
\varepsilon_t^2 = \frac{\alpha_0}{(1 - \alpha_1)} \quad (6.31)
\]
Finally we can conclude that equation 6.30 (i.e. mathematical expression of conditional heteroscedasticity disturbances) yields the same result as the unconditional autoregressive process of \( \varepsilon_t \) since we employ the properties of constant variance, zero mean, and all auto-covariances are zero. However, this is not the case for conditional autoregressive process of variance, where,

\[
E \varepsilon_t^2 = E \varepsilon_{t-1}^2 \neq E \varepsilon_{t-2}^2 \neq \ldots \neq E \varepsilon_{t-k}^2 \text{ and } \sigma_t^2 = 1
\]

Finally the conditional variance can be derived from the following equation:

\[
E(\varepsilon_t^2 | \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2,
\]

where,

\[
E(\varepsilon_{t-1}^2 | \varepsilon_{t-2}, \varepsilon_{t-3}, \ldots) = \alpha_0 + \alpha_1 \varepsilon_{t-2}^2,
\]

Since the \([\varepsilon_t]\) follows a conditional heteroscedastic process, the \([y_t]\) will be in the autoregressive conditional heteroscedasticity (ARCH) as well. Finally, we conclude that the ARCH model can reflect the volatility of the time series \([y_t]\).

To simplify the discussion above, we used the ARCH(1) as an example. However, the ARCH of a variance process may follow a \(q\) order which can be shown in the following equation:

\[
\sigma_t^2 = \nu_t^2 (\alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2)
\]

\[
\varepsilon_t = \sqrt{\alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2}
\]

The equation above is the same as a model of a time-varying parameter with MA(q).
Bollerslev (1986) expands Engle’s work by considering an AR process in the heteroscedasticity of variances called generalised autoregressive heteroscedasticity (GARCH). In mathematical form, GARCH can be shown in the following equation:

\[ \sigma_t^2 = \nu_t^2 \left( \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \right) \]  

(6.35)

where,

The MA (q) process of residuals is

\[ \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 = \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 \]

The AR(p) process of variances is

\[ \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 = \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \ldots + \beta_p \sigma_{t-p}^2 \]

since \( \nu_t^2 = 1 \) and \( \sigma_t^2 = \left( \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \right) \)

When the variances (\( \sigma_t^2 \)) are heteroscedastic, we can replace the symbol \( \sigma_t^2 \) with \( h_t \) (i.e. heteroscedasticity).

To test time variance in variances, this study employs the LM test on the ARMA(1,1) variances. The mathematical background to this test is given in Appendix 6.9. 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). Additionally we can also adopt the Ljung-Box q-statistics on the residuals of mean process to test the ARCH process (see the discussion in paragraph 6.4.1).

### 6.6.3. Model selection procedures in GARCH

To select the GARCH models is not straightforward. This study adopts the following procedure: (1) identify the patterns of data (i.e. stationarity and trend); (2) transform the non-stationary data time series into a stationary process if necessary; (3) identify the mean.
processes (AR, MA and ARMA); (4) test the ARCH process; (5) test the GARCH process. Steps 1 and 2 have been discussed in section 6.4 in this chapter. The following section will discuss the identification of AR, ARMA, ARCH and GARCH processes.

To identify the AR process, we can use the PACF of the series. The high PACF score in certain lags, which are measured by the q-statistic of Box-Pierce or Ljung-Box, indicates the presence of the AR process. Based on the certain lags which have significant scores, we can employ those significant lags as parameters (i.e. AR) in regression. However, this method needs an iterative process to choose the true AR process until the process achieves efficient estimates. Some model selection indicators can be employed, such as AIC and SBC (see Appendix 6.1). \( R^2 \) is less appropriate for this purpose because the \( R^2 \) will increase when more parameters are included in the regression. The correlogram of ACF and PACF provides an initial guess of the ARMA process. The detail of these guidelines is in Appendix 6.1.

The next step is to identify the MA process. The AR process will produce residuals which are the difference between the actual series and the forecasts. Based on these residuals, we regress the time series \( (y_t) \) on residuals \( (e_t) \). To obtain the initial guess for the lags of the MA process \( (e_t) \) in this regression, we can use the ACF and PACF correlogram of residuals. The method to derive the correlogram on residuals is similar to that in the original series. Since we have identified the MA process, this MA with lag “q” will be incorporated into the AR models. To select the best ARMA models, we employ several rules of statistical properties such as AIC and SBC. Additionally, this study also considers the parsimony principle as suggested by Box-Jenkins (1976). This principle suggests that the models will produce a better fit with the data if no additional unnecessary parameters (i.e. insignificant parameters) are added. To ensure that the model is parsimonious, the t-statistic must be greater than 1.96 (i.e. the coefficient must be statistically different from zero at a 5% confidence level). Finally, the efficient estimate of the ARMA process can be achieved by employing the least-squares estimation procedure.
Chapter 6 - Foreign Exchange Rate Risk Assessment Using Alternative Models: Empirical evidence

The next step is to identify the ARCH process. The Lagrange Multiplier (LM) test is the most widely used to detect the ARCH process on mean residuals. Engle (1982) adopts this test by employing the following steps:

1. Use OLS to estimate the most appropriate AR(n) model:
   \[ y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_n y_{t-n} + \varepsilon_t \]
2. Obtain the squares of the fitted errors \( \hat{\varepsilon}_t^2 \). Regress these squared residuals on a constant and on the “q” lagged values (\( \hat{\varepsilon}_t = a_0 + a_1 \hat{\varepsilon}_{t-1} + a_2 \hat{\varepsilon}_{t-2} + \ldots + a_q \hat{\varepsilon}_{t-q} \)).

If there is no ARCH or GARCH effect, the estimated values of \( \alpha_1, \alpha_2, \ldots, \alpha_q \) will be zero. Hence, this regression will have little explanatory power so the coefficient of determination (i.e., the usual R²-statistic) will be quite low. With a sample of T residuals and under the null hypothesis of no ARCH errors, the large TR² (i.e. over the \( \chi^2_q \) distribution) provides evidence for the rejection of this hypothesis.

The next step is to identify the GARCH process. Actually, the GARCH process is similar to the AR process in ARIMA models. To obtain an initial guess of the GARCH process, we can use the same approach as that used in the AR process by regressing the estimates of ARCH on the ARCH residuals with certain lags. The significant coefficients of lagged residuals is the preliminary identification of the GARCH process, and can be included in the models. Using AIC and SBC, we can identify the efficient parameters of the GARCH models.

6.7. Empirical results

Based on the procedures which have been discussed in section 6.6, we find that 11 series have zero means and 7 series have non-zero means. The series with zero mean indicate that the series are white noise and support the conclusion that these series are generated from stationary processes. All series are generated from ARCH processes while only 6
series are generated from GARCH processes. Details of the models are provided in the following table:

### Table 6.5
**Means and Heteroscedasticity Process of Variance Models**

<table>
<thead>
<tr>
<th>No.</th>
<th>Currency</th>
<th>Mean Process</th>
<th>Conditional Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>ATS</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.21 + 0.17\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>2</td>
<td>AUD</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.14 + 0.13\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>3</td>
<td>BEF</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.10 + 0.04\varepsilon_{t-1}^2 + 0.65\sigma_{t-1}^2$</td>
</tr>
<tr>
<td>4</td>
<td>BND</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.13 + 0.28\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>5</td>
<td>CAD</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.31 + 0.26\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>6</td>
<td>CHF</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.35 + 0.14\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>7</td>
<td>DEM</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.28 + 0.21\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>8</td>
<td>DKK</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.21 + 0.15\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>9</td>
<td>FFR</td>
<td>$y_t = -0.57y_{t-1} + \varepsilon_t$</td>
<td>$h_t = 0.06 + 0.13\varepsilon_{t-1}^2 + 0.7\sigma_{t-1}^2$</td>
</tr>
<tr>
<td>10</td>
<td>GBP</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.06 + 0.14\varepsilon_{t-1}^2 + 0.59\varepsilon_{t-1}^2 + 0.1\sigma_{t-1}^2$</td>
</tr>
<tr>
<td>11</td>
<td>HKD</td>
<td>$y_t = 0.02 + \varepsilon_t$</td>
<td>$h_t = 0.03 + 0.24\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>12</td>
<td>ITL</td>
<td>$y_t = -0.14y_{t-1} + \varepsilon_t$</td>
<td>$h_t = 0.02 + 0.11\varepsilon_{t-1}^2 + 0.84\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>13</td>
<td>JPY</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.11 + 0.26\varepsilon_{t-1}^2 + 0.41\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>14</td>
<td>MYR</td>
<td>$y_t = 0.03 - 0.16y_{t-1} + \varepsilon_t$</td>
<td>$h_t = 0.03 + 0.58\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>15</td>
<td>NLG</td>
<td>$y_t = -0.23y_{t-1} + 0.11\varepsilon_{t-1} + \varepsilon_t$</td>
<td>$h_t = 0.25 + 0.54\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>16</td>
<td>NZD</td>
<td>$y_t = -0.18y_{t-1} + \varepsilon_t$</td>
<td>$h_t = 0.01 + 0.11\varepsilon_{t-1}^2 + 0.85\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>17</td>
<td>SEK</td>
<td>$y_t = 0 + \varepsilon_t$</td>
<td>$h_t = 0.23 + 0.15\varepsilon_{t-1}^2$</td>
</tr>
<tr>
<td>18</td>
<td>USD</td>
<td>$y_t = 0.02 - 0.34y_{t-1} + \varepsilon_t$</td>
<td>$h_t = 0.00 + 0.23\varepsilon_{t-1}^2$</td>
</tr>
</tbody>
</table>

Using those models, we estimate the IDR risk of returns for the next day (i.e. 2 June 1997) by employing one tail of a 5% confidence level with the assumption that the IDR exchange rate returns are normally distributed from their means. In mathematical terms, the estimates are calculated from the following equation:

$$\hat{y}_t = \bar{y}_t + 1.96\sigma_t$$

(6.36)

The estimates on 2 June 1997 are given in the following table:
<table>
<thead>
<tr>
<th>Curr.</th>
<th>Variances</th>
<th>Standard deviation</th>
<th>Conditional Mean</th>
<th>Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATS</td>
<td>0.32</td>
<td>0.56</td>
<td>0.00</td>
<td>-1.11</td>
</tr>
<tr>
<td>AUD</td>
<td>0.16</td>
<td>0.39</td>
<td>0.00</td>
<td>-0.77</td>
</tr>
<tr>
<td>BEF</td>
<td>0.28</td>
<td>0.53</td>
<td>0.00</td>
<td>-1.04</td>
</tr>
<tr>
<td>BND</td>
<td>0.14</td>
<td>0.37</td>
<td>0.00</td>
<td>-0.72</td>
</tr>
<tr>
<td>CAD</td>
<td>0.31</td>
<td>0.56</td>
<td>0.00</td>
<td>-1.09</td>
</tr>
<tr>
<td>CHF</td>
<td>0.51</td>
<td>0.72</td>
<td>0.00</td>
<td>-1.40</td>
</tr>
<tr>
<td>DEM</td>
<td>0.36</td>
<td>0.60</td>
<td>0.00</td>
<td>-1.18</td>
</tr>
<tr>
<td>DKK</td>
<td>0.29</td>
<td>0.54</td>
<td>0.00</td>
<td>-1.05</td>
</tr>
<tr>
<td>FRF</td>
<td>0.29</td>
<td>0.54</td>
<td>-0.29</td>
<td>-1.35</td>
</tr>
<tr>
<td>GBP</td>
<td>0.18</td>
<td>0.42</td>
<td>0.00</td>
<td>-0.82</td>
</tr>
<tr>
<td>HKD</td>
<td>0.51</td>
<td>0.71</td>
<td>0.02</td>
<td>-1.38</td>
</tr>
<tr>
<td>ITL</td>
<td>0.28</td>
<td>0.53</td>
<td>0.09</td>
<td>-0.95</td>
</tr>
<tr>
<td>JPY</td>
<td>0.22</td>
<td>0.47</td>
<td>0.00</td>
<td>-0.91</td>
</tr>
<tr>
<td>MYR</td>
<td>0.03</td>
<td>0.18</td>
<td>0.03</td>
<td>-0.32</td>
</tr>
<tr>
<td>NLG</td>
<td>0.46</td>
<td>0.68</td>
<td>0.14</td>
<td>-1.18</td>
</tr>
<tr>
<td>NZD</td>
<td>0.18</td>
<td>0.43</td>
<td>0.13</td>
<td>-0.71</td>
</tr>
<tr>
<td>SEK</td>
<td>0.24</td>
<td>0.49</td>
<td>0.00</td>
<td>-0.96</td>
</tr>
<tr>
<td>USD</td>
<td>0.00</td>
<td>0.03</td>
<td>0.02</td>
<td>-0.04</td>
</tr>
</tbody>
</table>

All estimates of negative exchange rate returns are less than 8% which is the figure suggested by the Banking Supervisory Committee (BIS) within the standardised method. Plots of the actual value and estimates using GARCH models are provided in the following graphs:
Graph 6.2.A
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

ATS

AUD

BEF

BND

CAD

CHF
Graph 6.2.B
Plot of GARCH Estimates Using a 5% Confidence Level

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>DEM</td>
<td>FFR</td>
<td>DKK</td>
<td>GBP</td>
</tr>
<tr>
<td>HKD</td>
<td>ITL</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

VI-44
Graph 6.2.C
Plot of GARCH Estimates Using a 5% Confidence Level

<table>
<thead>
<tr>
<th>Date Range</th>
<th>Currency</th>
<th>JPY</th>
<th>MYR</th>
<th>NLG</th>
<th>NZD</th>
<th>SEK</th>
<th>USD</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 January 1996 - 30 May 1997</td>
<td>JPY</td>
<td><img src="https://example.com/graph1.png" alt="Graph" /></td>
<td><img src="https://example.com/graph2.png" alt="Graph" /></td>
<td><img src="https://example.com/graph3.png" alt="Graph" /></td>
<td><img src="https://example.com/graph4.png" alt="Graph" /></td>
<td><img src="https://example.com/graph5.png" alt="Graph" /></td>
<td><img src="https://example.com/graph6.png" alt="Graph" /></td>
</tr>
<tr>
<td>3 June - 10 July 1997</td>
<td>MYR</td>
<td><img src="https://example.com/graph7.png" alt="Graph" /></td>
<td><img src="https://example.com/graph8.png" alt="Graph" /></td>
<td><img src="https://example.com/graph9.png" alt="Graph" /></td>
<td><img src="https://example.com/graph10.png" alt="Graph" /></td>
<td><img src="https://example.com/graph11.png" alt="Graph" /></td>
<td><img src="https://example.com/graph12.png" alt="Graph" /></td>
</tr>
<tr>
<td>2 January 1996 - 30 May 1997</td>
<td>NLG</td>
<td><img src="https://example.com/graph13.png" alt="Graph" /></td>
<td><img src="https://example.com/graph14.png" alt="Graph" /></td>
<td><img src="https://example.com/graph15.png" alt="Graph" /></td>
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<td><img src="https://example.com/graph17.png" alt="Graph" /></td>
<td><img src="https://example.com/graph18.png" alt="Graph" /></td>
</tr>
<tr>
<td>3 June - 10 July 1997</td>
<td>NZD</td>
<td><img src="https://example.com/graph19.png" alt="Graph" /></td>
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<td><img src="https://example.com/graph24.png" alt="Graph" /></td>
</tr>
<tr>
<td>2 January 1996 - 30 May 1997</td>
<td>SEK</td>
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<td><img src="https://example.com/graph26.png" alt="Graph" /></td>
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<td><img src="https://example.com/graph29.png" alt="Graph" /></td>
<td><img src="https://example.com/graph30.png" alt="Graph" /></td>
</tr>
<tr>
<td>3 June - 10 July 1997</td>
<td>USD</td>
<td><img src="https://example.com/graph31.png" alt="Graph" /></td>
<td><img src="https://example.com/graph32.png" alt="Graph" /></td>
<td><img src="https://example.com/graph33.png" alt="Graph" /></td>
<td><img src="https://example.com/graph34.png" alt="Graph" /></td>
<td><img src="https://example.com/graph35.png" alt="Graph" /></td>
<td><img src="https://example.com/graph36.png" alt="Graph" /></td>
</tr>
</tbody>
</table>
6.8. Testing of GARCH estimates

To examine the power of these models, we can compare the fraction of days when the actual volatility is higher than the GARCH estimate and the choice of confidence level in estimation. This error test examines the lower bound of estimates because the purpose of the estimates is simply to cover negative losses. Based upon this error test, the best achievement of GARCH models occurs in HKD, when this model fails to cover only 3 losses out of 350 observations (i.e. 0.86% errors), and the worst result occurs in DEM when 13 losses are uncovered by estimates (i.e. 3.71% errors). These errors are very close to the one tail confidence level of 2.5%. Appendix 6.12 shows the details of the error estimates for all currencies. However, there is an argument that this method attempts to compare risks from a static portfolio (i.e. exposure is assumed to be fixed for a certain time horizon) in this model and dynamic revenues in actual profit and loss. The GARCH model is more appropriate for a shorter time horizon (i.e. daily) when the portfolio doesn’t change too much. Based on the error estimates, the GARCH model produces the average percentage errors shown in Table 6.7. Based on this table, GARCH yields lower errors than EWMA.

Additionally, this section will employ Kupiec’s error tests to examine the accuracy of the GARCH estimates (Kupiec, 1995b). Initially, this method tests the accuracy of estimates according to time until first failure (TUFF). Assume $t$ is the time until first failure and $\bar{T}$ is a random variable which represents the number of days until the first failure. Let $p$ be the probability of a failure on any given day. The probability of observing the first failure on day $t$ is given by the following:

$$\text{Prob} (\bar{T} = t) = p(1-p)^{t-1}$$  \hspace{1cm} (6.37)

Kupiec suggests that $\bar{T}$ has a geometric distribution with an expected value $1/p$. For example, if $p$ is 0.02, the average time until the first failure is $1/0.02 = 50$. This method
will test whether the actual number of days until the first failure ($\bar{T}$) is statistically different from the null hypothesis. Kupiec adopts the Neyman-Person lemma to construct a log likelihood ratio (LR) test. Given $p = p^*$ (i.e. the null hypothesis), a value of $\bar{T}$ (assuming $\bar{T} = N$) and $p^*$, the LR test can be solved using the following equation:

$$LR(N, p^*) = -2\log[p^*(1 - p^*)^{N-1}] + 2\log \left[ \left( \frac{1}{N} \right) \left( \frac{1 - \frac{1}{N} }{N} \right)^{N-1} \right]$$

Under the null hypothesis, the value of $LR(N, p^*)$ has a chi-squared distribution with one degree of freedom. GARCH estimates in this study were calculated using a one tailed test with a 0.025 confidence level. Therefore, we employ $p^* = 0.025$ in this TUFF test. The results show that all currencies accept the null hypothesis (i.e. $p = p^* \rightarrow 1/0.025 = 40$). In other words, the true time until first failure is not different from 40 days. See Table 6.8 for more details. However, these results may accept a false hypothesis when the actual time until first failure is not 40 days. Kupiec classifies these errors as Type II error rates and he suggests testing with Kupiec Table 2 (see Appendix 6.21). The probability of accepting a false null hypothesis for each currency is shown in Appendix 6.17.

Additionally, Kupiec suggests using the total number of failures to test the accuracy of the estimates, especially when the test cannot reject the null hypothesis. Assume that the total number of observations is $T$, total number of failures is $N$, and the probability of a failure on any one of the independent trials is $p$. Kupiec suggests that the probability of observing $N$ failures in a sample size of $T$ follows a binomial process as shown in the following equation:

$$\text{Binomial}[T, N] = (1 - p)^{T-N} p^n$$

Using the same procedure as the TUFF test, the LR test statistic of the null hypothesis that $p = p^*$ can be shown in the following equation:
\[ LR = -2 \log \left[ (1 - p^*)^{r-N}(p^*) \right] + 2 \log \left[ 1 - \left( \frac{T}{N} \right)^{r-N} \left( \frac{T}{N} \right) \right]^N, \]  

(6.40)

where \( p^* \) is the probability of a failure under the null hypothesis. Under this test, the proportion of failures has a chi-squared distribution with one degree of freedom. Using \( p^* = 0.025 \) (i.e. the number of failure is 8.750), all currencies accept the null hypothesis that the number of actual failures is not statistically different from the null hypothesis with a 5% confidence level - see Appendix 6.20 for details. Additionally, this study makes a simulation using alternative values for \( p^* \). The results show that the larger the difference of \( p^* \) from 0.025, the more the test results in rejection. Finally, we can be confident that the GARCH models used in this study provide estimates with a level of accuracy of 97.5%.
Table 6.7

<table>
<thead>
<tr>
<th>Currencies</th>
<th>Number of Obs.</th>
<th>%</th>
<th>Number of Obs.</th>
<th>%</th>
<th>Number of Obs.</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATS</td>
<td>8</td>
<td>2.29</td>
<td>9</td>
<td>2.57</td>
<td>14</td>
<td>4.00</td>
</tr>
<tr>
<td>AUD</td>
<td>12</td>
<td>3.43</td>
<td>11</td>
<td>3.14</td>
<td>12</td>
<td>3.43</td>
</tr>
<tr>
<td>BEF</td>
<td>10</td>
<td>2.86</td>
<td>12</td>
<td>3.43</td>
<td>14</td>
<td>4.00</td>
</tr>
<tr>
<td>BND</td>
<td>5</td>
<td>1.43</td>
<td>7</td>
<td>2.00</td>
<td>4</td>
<td>1.14</td>
</tr>
<tr>
<td>CAD</td>
<td>7</td>
<td>2.00</td>
<td>10</td>
<td>2.86</td>
<td>7</td>
<td>2.00</td>
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<tr>
<td>CHF</td>
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<td>2.86</td>
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<td>2.57</td>
<td>13</td>
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</tr>
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<td>12</td>
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<td>10</td>
<td>2.86</td>
<td>10</td>
<td>2.86</td>
<td>11</td>
<td>3.14</td>
</tr>
<tr>
<td>JPY</td>
<td>8</td>
<td>2.29</td>
<td>12</td>
<td>3.43</td>
<td>12</td>
<td>3.43</td>
</tr>
<tr>
<td>MYR</td>
<td>8</td>
<td>2.29</td>
<td>18</td>
<td>5.14</td>
<td>12</td>
<td>3.43</td>
</tr>
<tr>
<td>NLG</td>
<td>11</td>
<td>3.14</td>
<td>9</td>
<td>2.57</td>
<td>8</td>
<td>2.29</td>
</tr>
<tr>
<td>NZD</td>
<td>12</td>
<td>3.43</td>
<td>12</td>
<td>3.43</td>
<td>11</td>
<td>3.14</td>
</tr>
<tr>
<td>SEK</td>
<td>10</td>
<td>2.86</td>
<td>10</td>
<td>2.86</td>
<td>10</td>
<td>2.86</td>
</tr>
<tr>
<td>USD</td>
<td>6</td>
<td>1.71</td>
<td>13</td>
<td>3.71</td>
<td>26</td>
<td>7.43</td>
</tr>
<tr>
<td>Sum</td>
<td>162</td>
<td>46.29</td>
<td>202</td>
<td>57.71</td>
<td>213</td>
<td>60.86</td>
</tr>
<tr>
<td>Average</td>
<td>9</td>
<td>2.57</td>
<td>11.22</td>
<td>3.21</td>
<td>11.83</td>
<td>3.38</td>
</tr>
</tbody>
</table>

Note: *) 8/350x100
DF = Decay factor

However, to estimate the GARCH models needs some expertise which is not always available in banks, even in banking supervision units in central banks. Moreover, forecasting in GARCH models is more complicated and requires experience as well as technical skill, such as the sharpness of intuition to observe the patterns of data and the skill to generate efficient models. Therefore, there is no guarantee that two experts in forecasting will produce the same models for GARCH even if they employ the same data.
Regulatory authorities must be aware of the weaknesses of GARCH models. The adoption of GARCH for internal models in banks will require thorough examination before banks are allowed to employ GARCH for capital adequacy purposes.

6.9. Foreign exchange risk assessment using GARCH volatility and correlation

This section will employ the estimates of IDR (negative) returns in foreign exchange exposure of a sample bank in Indonesia to assess its foreign exchange risk and compare the results to those calculated using the standardised method of the 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 risk diversification theory (see Chapter 4 for details), the volatility of one currency may affect 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:

\[ \rho_{ij,t} = \frac{\rho_{ij,t}}{\sqrt{\rho_{ii,t} * \rho_{jj,t}}} \]  \hspace{0.5cm} (6.41)

where,

\( \rho_{ij,t} \) = 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 correlation matrices of variances is given in Appendix 6.14.

The results of risk assessment using one tail of a 5% confidence level are given in the following table:

VI-50
### Table 6.8
**Foreign Exchange Risk of a Sample Bank**

<table>
<thead>
<tr>
<th>Currencies</th>
<th>Net Position</th>
<th>GARCH estimates</th>
<th>DaR using GARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATS</td>
<td>1,236,858</td>
<td>-1.106</td>
<td>(13,675)</td>
</tr>
<tr>
<td>AUD</td>
<td>6,107,616</td>
<td>-0.773</td>
<td>(47,233)</td>
</tr>
<tr>
<td>BEF</td>
<td>488</td>
<td>-1.045</td>
<td>(5)</td>
</tr>
<tr>
<td>BND</td>
<td>23,934</td>
<td>-0.723</td>
<td>(173)</td>
</tr>
<tr>
<td>CAD</td>
<td>334,553</td>
<td>-1.095</td>
<td>(3,662)</td>
</tr>
<tr>
<td>CHF</td>
<td>1,532,204</td>
<td>-1.404</td>
<td>(21,505)</td>
</tr>
<tr>
<td>DEM</td>
<td>6,422,919</td>
<td>-1.175</td>
<td>(75,499)</td>
</tr>
<tr>
<td>DKK</td>
<td>425,981</td>
<td>-1.050</td>
<td>(4,475)</td>
</tr>
<tr>
<td>FFR</td>
<td>1,799,277</td>
<td>-1.346</td>
<td>(24,214)</td>
</tr>
<tr>
<td>GBP</td>
<td>34,886,948</td>
<td>-0.823</td>
<td>(287,086)</td>
</tr>
<tr>
<td>HKD</td>
<td>9,021,071</td>
<td>-1.381</td>
<td>(124,592)</td>
</tr>
<tr>
<td>ITL</td>
<td>77,882,972</td>
<td>-0.950</td>
<td>(740,132)</td>
</tr>
<tr>
<td>JPY</td>
<td>3,790,421,766</td>
<td>-0.913</td>
<td>(34,608,476)</td>
</tr>
<tr>
<td>MYR</td>
<td>14,996,934</td>
<td>-0.323</td>
<td>(48,367)</td>
</tr>
<tr>
<td>NLG</td>
<td>1,219,866</td>
<td>-1.184</td>
<td>(14,446)</td>
</tr>
<tr>
<td>NZD</td>
<td>240,219</td>
<td>-0.705</td>
<td>(1,695)</td>
</tr>
<tr>
<td>SEK</td>
<td>320,558</td>
<td>-0.963</td>
<td>(3,087)</td>
</tr>
<tr>
<td>USD</td>
<td>643,608,560</td>
<td>-0.039</td>
<td>(249,649)</td>
</tr>
</tbody>
</table>

Daily at Risk (DaR) (36,267,970)
Diversified Daily at Risk (DDaR) (34,958,455)

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 (see Table 6.1), EWMA with original decay factors requires IDR 72,793,852 thousand, EWMA with a 0.94 decay factor requires IDR 72,437,750 thousand (see Table 6.3), 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>
<thead>
<tr>
<th>Models</th>
<th>Risk</th>
<th>After multiplying by 3</th>
<th>The difference from the standardised method</th>
</tr>
</thead>
<tbody>
<tr>
<td>GARCH</td>
<td>34,958,455</td>
<td>104,875,365</td>
<td>365,290,374-104,875,365 =260,415,009</td>
</tr>
<tr>
<td>BIS</td>
<td>365,290,374</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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.

6.10. Conclusions

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 (see Table 6.7).

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)\(^{20}\). 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.

\(^{20}\) 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.
Chapter 7
Conclusions

After the bank reform of 1988, the regulatory authorities in Indonesia relied heavily on minimum capital requirements to curb excessive risk taking by banks by adopting the Basle Accord of 1988. However, this minimum capital regulation failed to prevent bank failure - witness the many banks that failed in Indonesia after 1989- because the regulation considered only credit risk. Additionally, the methodology for assessing credit risk in the Basle Accord of 1988 is flawed. Moreover, in general, the credit risks of borrowers in Indonesia are higher than those in the BIS's member countries. For these reasons, a re-evaluation of the effectiveness of the then current capital adequacy regulation was in order.

Many types of risk may affect the economic value of capital, such as credit risk, market risk (i.e. interest rate risk, foreign exchange rate risk, price risk for equities and commodities), operational risk and other risks. The empirical work conducted in this thesis concerning the determinants of problem banks in Indonesia finds that banks in Indonesia are sensitive mainly to credit risk, interest rate risk, liquidity risk and operational risk. It also finds that foreign exchange rate risk is insignificant for problem banks (when grouped together) in Indonesia. However, this finding does not mean that no Indonesian bank has faced problems because of foreign exchange rate risk. Because so few banks suffered from foreign exchange rate risk, the parameter which represents this risk is not significant. However, if we observe individual cases of bank failure, we find that some banks, such as Bank Duta in 1990 and Bank Exim in 1997, encountered severe financial difficulties because of huge losses in foreign exchange trading. It is thus clear that some banks failed because of foreign exchange rate risk, although the number is very low compared to the number of banks which failed because of other risks. Therefore, further examination of foreign exchange risk exposure was in order.
Chapter 7 - Conclusions

The insignificance of the foreign exchange rate risk parameter is consistent with the fact that most failed banks were unauthorised in foreign exchange transactions. Even though the number of authorised foreign exchange banks is low, they account for a large portion of market share. Seven state banks (all foreign exchange banks) control 40% of the market in credit while foreign exchange banks in general account for around 70% of the market in credit (Bank Indonesia, 1995). Therefore, the failure of a foreign exchange bank will affect the banking system in Indonesia significantly. This study thus concludes that the inclusion of market risk (predominantly foreign exchange rate risk) in capital adequacy assessment in Indonesia is necessary.

The models in Chapter 3 can also be used as an “early warning system” by banking supervisors as they allow for the early identification of potentially problematic banks. However, due to the current banking crisis in Indonesia, these models require adjustment using new financial data because the financial ratios after the crisis may produce different coefficients of parameters. Using error I type and error II type tests, the model 2 in Chapter 3 can estimate problem banks with only 12.38% total errors. This figure is better than that achieved by most researchers, including Espahbodi (1991) who produced 16.89% errors. The errors in this study mostly occur during the transition period when banks are re-classified from non-problem to problem or from problem to non-problem. This is possibly because the regulatory authority needs time to classify banks as problems although the financial reports in the previous quarter had already shown that the banks were in trouble.

The empirical study in Chapter 3 employed data of call reports and supervisory information in Bank Indonesia. The data and information are available only for banking supervision purposes. Therefore, the use of the data in the model will yield reliable results for an early warning system in banking supervision.
The simulation of these GARCH volatilities into the foreign exchange positions of a bank in Indonesia shows that the inclusion of foreign exchange rate risk in capital adequacy assessment makes the bank's capital ratio break the trigger of the minimum requirement. However, the inclusion of market risk within capital adequacy regulations requires thorough study of the methodology of risk assessment and of the requirements appropriate for banks interested in using internal models. The adoption of internal models may create the following problems: (1) inequality in the standards used for the verification of internal models will discourage convergence in capital adequacy regulation; (2) a relaxed approach to the supervisory recognition of internal models or the adoption of the pre-commitment approach (PCA) may induce banks to set capital requirements as low as possible and to ignore the true risks. This may render the minimum capital adequacy regulation ineffective.
Bibliography


Bibliography


McNew, L.,(1997). "Do it by the book", Risk, June, pp.52-7


Appendix 2.1
Pseudo-R²

Aldrich & Nelson (1984, pp.55-7):

\[
Pseudo \ R^2 = \frac{c}{(N + c)}
\]

where,
\(c\) = the chi-square statistic for overall fit (log likelihood ratio) which can be derived from the following equation:
\(c = -2(l_m - l_o)\)
\(N\) = the total sample size
\(l_m\) = the log likelihood value of the model
\(l_o\) = the log likelihood value if all slope coefficients are restricted to zero

McFadden (1973, p.121):

\[
Pseudo \ R^2 = 1 - \frac{l_m}{l_o}
\]

McKelvey and Zavoina (1975, pp.103-20):

\[
Pseudo \ R^2 = \frac{\sum_{i=1}^{N} (\hat{\gamma}_i - \bar{F})^2}{\sum_{i=1}^{N} (\hat{\gamma}_i - \bar{F})^2 + N\hat{\sigma}^2} = \frac{ExSS}{ExSS + N\hat{\sigma}^2}
\]

where,
\(\bar{F} = \frac{1}{N} \sum \hat{\gamma}_i\)
\(\hat{\gamma}_i = x_i^\prime \hat{\beta}\) (ie. evaluated at maximum likelihood)
ExSS = the explained sum of square
\(\hat{\sigma}\) = the standard deviation of disturbance under the normal distribution assumption.

In a logit model this standard deviation is 1.814 (variance=3.29).
Appendix 4.1

Derivation of Capital Base Under the BIS Proposals

I. Components of capital

Tier 1 (primary capital):
1. Ordinary paid-up share capital/common stock
2. Disclosed reserves

Tier 2 (Supplementary capital):
1. Undisclosed reserves
2. Asset revaluation reserves
3. General provisions/general loan loss reserves
4. Hybrid (debt/equity) capital instruments
5. Subordinated term debt

II. Limitations

The sum of Tier 1 and Tier 2 elements will be eligible for inclusion in the capital base, subject to the following limits:
1. The total of Tier 2 elements will be limited to a maximum of 100 per cent of the total of Tier 1 elements (i.e. at least 50 per cent of the capital base must comprise Tier 1 elements)
2. Subordinated term debt will be limited to a maximum of 50 per cent of Tier 1 elements (i.e. 25 per cent of the capital base).
3. Where general provisions/general loan loss reserves include amounts reflecting lower valuations of assets or latent but unidentified losses present in the balance sheet, the amount of such provisions or reserves will be limited to a maximum of 1.25 percentage points, or exceptionally and temporarily up to 2.0 percentage points, of risk assets¹.
4. Asset revaluation reserves which take the form of latent gains on unrealised securities (see below) will be subject to a discount of 55 per cent.

III. Adjustment made to the capital base for calculation of the risk asset ratio

Deduction from Tier 1: goodwill
Deduction from total capital
1. Investment in unconsolidated banking and financial subsidiary companies (NB. The presumption is that the framework would be applied on a consolidated basis to banking groups)
2. Investment in the capital of other banks and financial institutions (at the discretion of national authorities).

¹ This limit would only apply in the event that no agreement is reached on a consistent basis for including unencumbered provisions or reserves in capital.
Appendix 4.2
Risk Weights by Category of On-balance-sheet Assets Under the BIS Proposals

<table>
<thead>
<tr>
<th>Percentage</th>
<th>Description</th>
</tr>
</thead>
</table>
| 0%        | (1) Cash  
(2) Balances at and claims on domestic central banks  
(3) Securities issued by domestic central governments¹  
(4) Loans and other assets fully collateralised by cash or domestic central government securities or fully guaranteed by domestic central governments² |
| 0 or 20%  | (1) Claims on IBRD and regional development banks (at national discretion) (EC countries would treat EC institutions consistently) |
| 20%       | (1) Claims on domestic and foreign banks with an original maturity of under one year  
(2) Claims on domestic banks with an original maturity of one year and over and loans guaranteed by domestic banks  
(3) Claims on foreign central governments in local currency financed by local currency liabilities  
(4) Cash items in process of collection |
| 20% or 50%| (5) Claims on the domestic public sector, excluding central government (at national discretion) and loans guaranteed by such institutions |
| 50%       | (6) Loans to owner-occupiers for residential house purchase fully secured by mortgage |
| 100%      | (7) Claims on the private sector  
(8) Cross-border claims on foreign banks with an original maturity of one year and over  
(9) Claims on foreign central governments (unless 20 per cent)  
(10) Claims on commercial companies owned by the public sector  
(11) Premises, plant and equipment and other fixed assets  
(12) Real estate and other investments (including non-consolidated investment participations in other companies)  
(13) Capital instruments issued by other banks (unless deducted from capital)  
(14) All other assets |

¹ The information stated below is derived from "Handbook of Banking Regulation and Supervision" by Maximilian JB. Hall, London: Woodhead-Faulkner, 1993, p.36
² National supervisors have the discretion to prescribe non-zero weights (e.g. 10 per cent or 20 per cent) if they attempt to take account of the investment risk on securities issued by their domestic central governments.
### APPENDIX 4.3
CREDIT CONVERSION FACTORS FOR OFF-BALANCE-SHEET ITEMS UNDER THE BIS PROPOSALS

<table>
<thead>
<tr>
<th>Instruments</th>
<th>Credit conversion factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Direct credit substitutes, e.g. general guarantees of indebtedness (including standby letters of credit serving as financial guarantees for loans and securities) and acceptances (including endorsements with the character of acceptances)</td>
<td>100%</td>
</tr>
<tr>
<td>2. Certain transaction-related contingent items (e.g. performance bonds, bid bonds, warranties and standby letters of credit related to particular transactions)</td>
<td>50%</td>
</tr>
<tr>
<td>3. Short-term, self-liquidating, trade-related contingencies (such as documentary credits collateralised by the underlying shipments)</td>
<td>20%</td>
</tr>
<tr>
<td>4. Sale and repurchase agreements and asset sales with resource, where the credit risk remains with the bank</td>
<td>100%</td>
</tr>
<tr>
<td>5. Forward purchases, forward forward deposits and partly paid shares and securities, which represent commitments with certain drawdown</td>
<td>100%</td>
</tr>
<tr>
<td>6. Note issuance facilities and revolving underwriting facilities</td>
<td>50%</td>
</tr>
<tr>
<td>7. Other commitments (e.g. formal standby facilities and credit lines) with an original maturity exceeding one year</td>
<td>50%</td>
</tr>
<tr>
<td>8. Similar commitments with an original maturity of less than one year, or which can be cancelled at any time</td>
<td>0%</td>
</tr>
<tr>
<td>9. Foreign exchange and interest rate related items</td>
<td>Treated separately</td>
</tr>
</tbody>
</table>

NB. Member countries will have some limited discretion to allocate particular instruments into items 1 to 8 above according to the characteristics of the instruments in the national market.


2 These items are to be weighted according to the type of asset and not according to the type of counterparty with whom the transaction has been entered into.
### Appendix 4.4

**Specific Risk-weights for Debt Securities Under the BIS Proposals**

<table>
<thead>
<tr>
<th>Securities</th>
<th>Description</th>
<th>Risk weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Government</td>
<td>Securities issued by government including bonds, treasury bills and other short-term instruments. Foreign government securities: specific risk subject to national discretion of each supervisor</td>
<td>0%</td>
</tr>
</tbody>
</table>
| Qualifying | Securities issued by public sector entities, multilateral development banks, and other securities which satisfy one of the following characteristics:  
1. Rated investment grade by at least two rating agencies specified by the relevant supervisors; or  
2. Rated investment-grade by one rating agency and not less than investment-grade by any other rating agency  
3. Unrated, but deemed to be of comparable investment quality by the bank or securities firm, and the issuer has securities listed on a recognized stock exchange (subject to supervisory approval) | 0.25% for residual maturity 6 months or less; or 1.0% for residual maturity between 6 and 24 months; or 1.6% for residual maturity exceeding 24 months |
| Other      | Securities which don’t cover two categories above fall in to “other” classification                                                                                             | 8%                                                                           |

**Note:** National supervisory authority may charge more than 8% for particular securities.

**Source:** Basle Committee on Banking Supervision, “Amendment to The Capital Accord to Incorporate Market Risks”, January 1996.
# Appendix 4.5

**Debt Securities’ Risk Weights Under the BIS Proposals Using Maturity Method**

<table>
<thead>
<tr>
<th>Time-band</th>
<th>Time-band for coupon 3% or more</th>
<th>Time-band for coupon &lt; than 3%</th>
<th>Assumed change in yields*</th>
<th>% risk weight</th>
<th>Horizontal Offsetting/disallowance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Within the zone</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Between adjacent zones</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Between zones 1 and 3</td>
</tr>
<tr>
<td><strong>Zone 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>up to 1 month</td>
<td>up to 1 month</td>
<td>1.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>1 to 3 months</td>
<td>1 to 3 months</td>
<td>1.00</td>
<td>0.20</td>
<td>40</td>
</tr>
<tr>
<td>3</td>
<td>3 to 6 months</td>
<td>3 to 6 months</td>
<td>1.00</td>
<td>0.40</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>6 to 12 months</td>
<td>6 to 12 months</td>
<td>1.00</td>
<td>0.70</td>
<td></td>
</tr>
<tr>
<td><strong>Zone 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1 to 2 years</td>
<td>1 to 1.9 years</td>
<td>0.90</td>
<td>1.25</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2 to 3 years</td>
<td>1.9 to 2.8 years</td>
<td>0.80</td>
<td>1.75</td>
<td>30</td>
</tr>
<tr>
<td>7</td>
<td>3 to 4 years</td>
<td>2.8 to 3.6 years</td>
<td>0.75</td>
<td>2.25</td>
<td></td>
</tr>
<tr>
<td><strong>Zone 3</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>4 to 5 years</td>
<td>3.6 to 4.3 years</td>
<td>0.75</td>
<td>2.75</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>5 to 7 years</td>
<td>4.3 to 5.7 years</td>
<td>0.70</td>
<td>3.25</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>7 to 10 years</td>
<td>5.7 to 7.3 years</td>
<td>0.65</td>
<td>3.75</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>10 to 15 years</td>
<td>7.3 to 9.3 years</td>
<td>0.60</td>
<td>4.50</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>15 to 20 years</td>
<td>9.3 to 10.6 years</td>
<td>0.60</td>
<td>5.25</td>
<td>30</td>
</tr>
<tr>
<td>13</td>
<td>over 20 years</td>
<td>10.6 to 12 years</td>
<td>0.60</td>
<td>6.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>zero coupon bond:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>12 to 20 years</td>
<td></td>
<td>0.60</td>
<td>8.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>over 20 years</td>
<td></td>
<td>0.60</td>
<td>12.50</td>
<td></td>
</tr>
</tbody>
</table>

Note: *Assumed change in yield which is designed to cover about two standard deviations of one month's yield volatility in most major markets.

Source: Basle Committee on Banking Supervision, "Amendment to The Capital Accord to Incorporate Market Risks", January 1996.
### Appendix 4.6

**Debt Securities' Risk Weights Under the BIS Proposals Using Duration Method**

<table>
<thead>
<tr>
<th>No</th>
<th>Time-band</th>
<th>Duration weight</th>
<th>Assumed change in yields</th>
<th>Risk weight (%)</th>
<th>Vertical disallowance (%)</th>
<th>Horizontal offsetting/disallowance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>5</td>
<td>Column 5 = (4*3)</td>
</tr>
<tr>
<td>1</td>
<td>up to 1 month</td>
<td>Duration *</td>
<td>1</td>
<td>Duration x 1</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>1 to 3 months</td>
<td>Duration *</td>
<td>1</td>
<td>Duration x 1</td>
<td>5</td>
<td>40</td>
</tr>
<tr>
<td>3</td>
<td>3 to 6 months</td>
<td>Duration *</td>
<td>1</td>
<td>Duration x 1</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>6 to 12 months</td>
<td>Duration *</td>
<td>1</td>
<td>Duration x 1</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td><strong>Zone 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1 to 1.9 years</td>
<td>Duration *</td>
<td>0.9</td>
<td>Duration x 0.9</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>1.9 to 2.8 years</td>
<td>Duration *</td>
<td>0.8</td>
<td>Duration x 0.8</td>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td>7</td>
<td>2.8 to 3.6 years</td>
<td>Duration *</td>
<td>0.75</td>
<td>Duration x 0.75</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td><strong>Zone 2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>3.6 to 4.3 years</td>
<td>Duration *</td>
<td>0.75</td>
<td>Duration x 0.75</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>9</td>
<td>4.3 to 5.7 years</td>
<td>Duration *</td>
<td>0.7</td>
<td>Duration x 0.7</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>10</td>
<td>5.7 to 7.3 years</td>
<td>Duration *</td>
<td>0.65</td>
<td>Duration x 0.65</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>11</td>
<td>7.3 to 9.3 years</td>
<td>Duration *</td>
<td>0.6</td>
<td>Duration x 0.6</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>12</td>
<td>9.3 to 10.6 years</td>
<td>Duration *</td>
<td>0.6</td>
<td>Duration x 0.6</td>
<td>5</td>
<td>30</td>
</tr>
<tr>
<td>13</td>
<td>10.6 to 12 years</td>
<td>Duration *</td>
<td>0.6</td>
<td>Duration x 0.6</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>14</td>
<td>12 to 20 years</td>
<td>Duration *</td>
<td>0.6</td>
<td>Duration x 0.6</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>15</td>
<td>over 20 years</td>
<td>Duration *</td>
<td>0.6</td>
<td>Duration x 0.6</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

**Note:** *) Duration is calculated using modified duration for each instrument

**Source:** Basle Committee on Banking Supervision, "Amendment to The Capital Accord to Incorporate Market Risks", January 1996.
### Appendix 4.7
Treatment for Debt and Equity Options (Under the BIS Proposals)

<table>
<thead>
<tr>
<th>Cash position</th>
<th>Option position</th>
<th>Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long</td>
<td>Long put</td>
<td>Position risk would be the market value of the underlying security multiplied by the sum of specific and general market risk charges for the underlying less the amount the option is in the money (if any)</td>
</tr>
<tr>
<td></td>
<td>Long call</td>
<td>Same as above</td>
</tr>
<tr>
<td>Short</td>
<td>Long call</td>
<td>Same as above</td>
</tr>
<tr>
<td>Short</td>
<td>Long put</td>
<td>Same as above</td>
</tr>
</tbody>
</table>
| None          | Long call or put| 1. The market value of the underlying security multiplied by the sum of specific and general market risk charges for underlying  
                  2. The market value of the option                                      |

Source: Basle Committee on Banking Supervision, “Amendment to The Capital Accord to Incorporate Market Risks”, January 1996.
Appendix 4.8
Qualitative and Quantitative Standards
(Under the BIS Proposals)²

Qualitative standards

1. The bank should have an independent risk control unit that is responsible for the design and implementation of the bank's risk management system.
2. The unit should conduct a regular back-testing program, i.e. an ex-post comparison of the risk measure generated by the model against actual daily changes in portfolio value over longer periods of time, as well as hypothetical changes.
3. Board of directors and senior management should be actively involved in the risk control process and must regard risk control as an essential aspect of the business to which significant resources need to be devoted.
4. The bank's internal risk measurement model must be closely integrated into the day-to-day risk management process of the bank. Its output should accordingly be an integral part of the planning, monitoring and controlling of the bank's market risk profile.
5. The risk measurement system should be used in conjunction with internal trading and exposure limits. In this regard, trading limits should be related to the bank's risk management model in a manner that is consistent over time.
6. A routine and rigorous program of stress testing should be in place as a supplement to the risk analysis based on the day-to-day output of the bank's risk measurement model.
7. Banks should have a routine in place for ensuring compliance with a documented set of internal policies, control and procedures concerning the operation of the risk measurement system.
8. An independent review of the risk measurement system should be carried out regularly in the bank's own internal auditing process.

Quantitative Standards

1. Value-at-risk must be computed on a daily basis.
2. In calculating the value-at-risk, a 99th percentile, one-tailed confidence interval is to be used.
3. In calculating value-at-risk, an instantaneous price shock equivalent to a 10 day movement in prices is to be used, i.e. the minimum "holding period" will be 10 trading days.
4. The choice of historical observation period (sample period) for calculating value-at-risk must be a minimum length of one year.
5. Banks should update their data sets no less frequently than once every three months and should also reassess them whenever market prices are subject to material changes.
6. No particular type of model is prescribed. So long as each model used captures all the material risks run by the bank, banks will be free to use models based on such as variance-covariance matrices, historical simulation and Monte Carlo simulation.
7. Banks will have discretion to recognise empirical correlations within broad risk categories (e.g. interest rates, exchange rates, equity prices and commodity prices, including related options volatilities in each risk factor category).
8. Banks' models must accurately capture the unique risks associated with options within each of the broad risk categories. The following criteria apply to the measurement of options risk:
   a. Bank's models must capture the non-linear price characteristics of option positions
   b. Banks are expected to ultimately move towards the application of a full 10 day price shock to options positions or positions that display option-like characteristics
   c. Each bank's risk measurement system must have a set of risk factors that captures the volatilities of the rates and prices underlying option positions, i.e. vega risk.
9. Each bank must meet, on a daily basis, a capital requirement expressed as the higher of the following

² Source: Basle Committee on Banking Supervision, "Amendment to The Capital Accord to Incorporate Market Risks", January 1996.
alternatives:

a. Its previous day's value-at-risk number measured according to the parameters specified in this section, or

b. An average of the daily value-at-risk measures on each of the preceding 60 business days, multiplied by a multiplication factor

10. The multiplication factor will be set by individual supervisory authorities on the basis of their assessment of the quality of the bank’s risk management system, subject to an absolute minimum of 3.

11. Banks using models will be subject to a separate capital charge to cover the specific risk of interest rate related instruments and equity securities as defined in the standardised approach to the extent that this risk is not incorporated into their model.
Appendix 6.1
Identification Guidelines and Model Selection Criteria

1. Identification:

<table>
<thead>
<tr>
<th>Process</th>
<th>ACF</th>
<th>PACF</th>
</tr>
</thead>
<tbody>
<tr>
<td>White-noise</td>
<td>All ( \rho_k = 0 )</td>
<td>All ( \phi_q = 0 )</td>
</tr>
<tr>
<td>AR(1): ( \alpha &gt; 0 )</td>
<td>Direct exponential decay ( \rho_k = \alpha^k )</td>
<td>( \phi_1 = \rho_1; \phi_q = 0 ) for ( k \geq 2 )</td>
</tr>
<tr>
<td>AR(1): ( \alpha &lt; 0 )</td>
<td>Oscillating decay: ( \rho_k = \alpha^k )</td>
<td>( \phi_1 = \rho_1; \phi_q = 0 ) for ( q \geq 2 )</td>
</tr>
<tr>
<td>AR(p)</td>
<td>Decays toward zero. Coefficients may oscillate</td>
<td>Spikes through lag p. All ( \phi_q = 0 ) for ( q &gt; p )</td>
</tr>
<tr>
<td>MA(1): ( \beta &gt; 0 )</td>
<td>Positive spike at lag 1. ( \rho_k = 0 ) for ( k \geq 2 )</td>
<td>Oscillating decay: ( \phi_1 &gt; 0 )</td>
</tr>
<tr>
<td>MA(1): ( \beta &lt; 0 )</td>
<td>Negative spike at lag 1. ( \rho_k = 0 ) for ( k \geq 2 )</td>
<td>Decay: ( \phi_1 &lt; 0 )</td>
</tr>
<tr>
<td>ARMA(1,1)</td>
<td>Exponential decay beginning at lag 1. ( \text{Sign } \rho_1 = \text{sign}(\alpha_1 + \beta) )</td>
<td>Oscillating decay beginning at lag 1. ( \phi_1 = \rho_1 )</td>
</tr>
<tr>
<td>ARMA(1,1)</td>
<td>Oscillating decay beginning at lag 1. ( \text{sign } (\phi_1) = \text{sign } (\phi_1) )</td>
<td>Exponential decay beginning at lag 1. ( \phi_1 = \rho_1 ) and ( \text{sign } (\phi_q) = \text{sign } (\phi_q) )</td>
</tr>
<tr>
<td>ARMA(p,q)</td>
<td>Decay (either direct or oscillatory) beginning at lag q</td>
<td>Decay (either direct or oscillatory) beginning at lag p</td>
</tr>
</tbody>
</table>

Sources: Walter Enders (1995, p. 85)

Note:
- \( \alpha \) = coefficient of AR process
- \( \beta \) = coefficient of MA process
- \( \rho_k \) = autocorrelation function for \( k > 1 \)
- \( \phi_q \) = partial autocorrelation function for \( q > 1 \)

2. Model Selection Criteria

The most widely used of model selection criteria to achieve parsimonious model are Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBC). These methods are derived from the following formula (Enders, p. 88):

\[
\text{AIC} = T \ln(\text{SSE}) + 2n \\
\text{SBC} = T \ln(\text{SSE}) + n \ln(T)
\]

where,
- \( n \) = number of parameters estimated (ie. \( p + q + \text{constant term} \))
- \( T \) = number of usable observations [ie. total number of original observations - (\( p + q + \text{constant term} \))]
- \( \text{SSE} = \text{sum square errors} \)
Appendix 6.2
Mathematical Background of Dickey-Fuller Test

To test whether $\alpha_1 = 1$, we employ the following equation:

$$y_t = \alpha_1 y_{t-1} + \varepsilon_t$$

Subtracting $y_{t-1}$ from both sides to get the delta $y_t$:

$$\Delta y_t = \alpha_1 y_{t-1} - y_{t-1} + \varepsilon_t$$

$$= (\alpha_1 - 1)y_{t-1} + \varepsilon_t$$

However, we can add the deterministic elements which are an intercept ($\alpha_0$) and a drift term ($\beta$):

$$\Delta y_t = \alpha_0 + \beta t + (\alpha_1 - 1)y_{t-1} + \varepsilon_t$$

Assuming that $(\alpha_1 - 1) = \rho$, the hypothesis in this test ($H_0$) is $\rho = 0$
Appendix 6.3

Dickey-Fuller Test at Level of the Series

<table>
<thead>
<tr>
<th>No.</th>
<th>Variable</th>
<th>ADF-TEST</th>
<th>DATS(-1)</th>
<th>D(DATS(-1))</th>
<th>D(DATS(-2))</th>
<th>D(DATS(-3))</th>
<th>D(DATS(-4))</th>
<th>C</th>
<th>Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>ATS</td>
<td>(8.64)</td>
<td>(1.05)</td>
<td>(0.00)</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td></td>
<td>0.12</td>
<td>0.11</td>
<td>0.09</td>
<td>0.08</td>
<td>0.05</td>
<td>0.05</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Std. Error</td>
<td></td>
<td>(8.64)</td>
<td>(0.03)</td>
<td>0.35</td>
<td>0.28</td>
<td>0.57</td>
<td>0.29</td>
<td>(0.40)</td>
</tr>
<tr>
<td></td>
<td>t-Statistic</td>
<td></td>
<td>-</td>
<td>0.98</td>
<td>0.73</td>
<td>0.78</td>
<td>0.57</td>
<td>0.77</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>Prob.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>AUD</td>
<td>(8.71)</td>
<td>(1.03)</td>
<td>0.07</td>
<td>0.02</td>
<td>0.00</td>
<td>0.04</td>
<td>0.09</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td></td>
<td>0.12</td>
<td>0.11</td>
<td>0.09</td>
<td>0.07</td>
<td>0.05</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Std. Error</td>
<td></td>
<td>(8.71)</td>
<td>0.69</td>
<td>0.23</td>
<td>0.08</td>
<td>0.75</td>
<td>2.13</td>
<td>(2.02)</td>
</tr>
<tr>
<td></td>
<td>t-Statistic</td>
<td></td>
<td>-</td>
<td>0.49</td>
<td>0.82</td>
<td>0.95</td>
<td>0.45</td>
<td>0.03</td>
<td>0.04</td>
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<tr>
<td></td>
<td>Prob.</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>BEF</td>
<td>(8.56)</td>
<td>(1.05)</td>
<td>(0.02)</td>
<td>0.02</td>
<td>(0.00)</td>
<td>0.03</td>
<td>(0.03)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td></td>
<td>0.12</td>
<td>0.11</td>
<td>0.09</td>
<td>0.08</td>
<td>0.05</td>
<td>0.05</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Std. Error</td>
<td></td>
<td>(8.56)</td>
<td>(0.20)</td>
<td>0.18</td>
<td>(0.06)</td>
<td>0.50</td>
<td>(0.46)</td>
<td>(0.27)</td>
</tr>
<tr>
<td></td>
<td>t-Statistic</td>
<td></td>
<td>-</td>
<td>0.84</td>
<td>0.86</td>
<td>0.95</td>
<td>0.62</td>
<td>0.65</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td>Prob.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>BND</td>
<td>(11.20)</td>
<td>(2.28)</td>
<td>0.69</td>
<td>0.34</td>
<td>0.12</td>
<td>0.01</td>
<td>0.06</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td></td>
<td>0.20</td>
<td>0.18</td>
<td>0.14</td>
<td>0.10</td>
<td>0.05</td>
<td>0.05</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Std. Error</td>
<td></td>
<td>(11.20)</td>
<td>3.87</td>
<td>2.42</td>
<td>1.28</td>
<td>0.25</td>
<td>1.25</td>
<td>(0.44)</td>
</tr>
<tr>
<td></td>
<td>t-Statistic</td>
<td></td>
<td>-</td>
<td>0.00</td>
<td>0.02</td>
<td>0.21</td>
<td>0.80</td>
<td>0.21</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>Prob.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>CAD</td>
<td>(11.52)</td>
<td>(2.32)</td>
<td>0.73</td>
<td>0.39</td>
<td>0.19</td>
<td>0.07</td>
<td>0.04</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td></td>
<td>0.20</td>
<td>0.18</td>
<td>0.14</td>
<td>0.10</td>
<td>0.05</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Std. Error</td>
<td></td>
<td>(11.52)</td>
<td>4.14</td>
<td>2.74</td>
<td>1.90</td>
<td>1.33</td>
<td>0.55</td>
<td>(0.03)</td>
</tr>
<tr>
<td></td>
<td>t-Statistic</td>
<td></td>
<td>-</td>
<td>-</td>
<td>0.01</td>
<td>0.06</td>
<td>0.19</td>
<td>0.59</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>Prob.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>CHF</td>
<td>(8.14)</td>
<td>(1.05)</td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.06)</td>
<td>(0.02)</td>
<td>(0.05)</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td></td>
<td>0.13</td>
<td>0.12</td>
<td>0.10</td>
<td>0.08</td>
<td>0.05</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Std. Error</td>
<td></td>
<td>(8.14)</td>
<td>(0.71)</td>
<td>(0.69)</td>
<td>(0.69)</td>
<td>(0.42)</td>
<td>(0.70)</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>t-Statistic</td>
<td></td>
<td>-</td>
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*MacKinnon critical values for rejection of hypothesis of a unit root.

1% Critical Value* -3.9872
5% Critical Value -3.4239
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Appendix 6.4

Test of Whitenoise using Ljung-Box and Box-Pierce

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**Note:**
- LB=Ljung-Box
- BP=Box-Pierce
- ACF=Autocorrelation function
- PACF=Partial autocorrelation function
Appendix 6.5

Distribution of IDR Exchange Rate Returns
(2 January 1996 - 30 May 1997)
Appendix 6.5
Distribution of IDR Exchange Rate Returns
(2 January 1996 - 30 May 1997)
Appendix 6.6
Solving Parameters of Autoregressive (AR) Process

AR(1) process.

Based on the Yule-Walker equation, the ACF at lag 1 is as follows:
\[ \rho_1 = \phi_1 \]
Assuming the empirical of ACF of \( \rho_1 = A_1 \), the parameter of AR(1) equals \( A \)

AR(2) process.

Based on the Yule-Walker equation, the ACF at lag 2 is as follows:
\[ \rho_1 = \phi_1 + \phi_2 \rho_1 \]
\[ \rho_2 = \phi_2 + \phi_1 \rho_2 \]
Replacing \( \rho_1 \) by \( A_1 \) and \( \rho_2 \) by \( A_2 \), we can solve for \( \phi_1 \) and \( \phi_2 \):
\[ A_1 = \phi_1 + \phi_2 A_1 \]
\[ A_2 = \phi_2 A_1 + \phi_1 \]
Rearranging these equations, we obtain the following equations:
\[ \phi_1 = A_1 - \phi_2 A_1 \]
\[ = A_1 (1 - \phi_2) \]
\[ \phi_2 = A_2 - \phi_1 A_1 \]
Inserting equation no. 1 into no. 2 and solving for \( \phi_2 \):
\[ \phi_2 = A_2 - A_1 (1 - \phi_2) A_1 \]
\[ = A_2 - (A_1 + A_1 \phi_2) A_1 \]
\[ = A_2 - A_1^2 + A_1^2 \phi_2 \]
\[ \phi_2 - A_1^2 \phi_2 = A_2 - A_1^2 \]
\[ \phi_2 (1 - A_1^2) = A_2 - A_1^2 \]
\[ \phi_2 = \frac{A_2 - A_1^2}{1 - A_1^2} \]
Inserting equation no. 2 into no. 1 and solving for \( \phi_1 \):
\[ \phi_1 = A_1 (1 - A_2 - \phi_1 A_1) \]
\[ = A_1 - A_1 A_2 - \phi_1 A_1^2 \]
\[ \phi_1 + \phi_1 A_1^2 = A_1 - A_1 A_2 \]
\[ \phi_1 (1 + A_1^2) = A_1 (1 - A_2) \]
\[ \phi_1 = \frac{A_1 (1 - A_2)}{1 + A_1^2} \]
Parameters of the higher order of AR process can be solved using the same approach.
Appendix 6.7
Mathematical Explanation of Moving Average (MA) Process

The MA process with order q can be written as:
\[ y_t = e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_3 e_{t-3} + \ldots + \theta_q e_{t-q} \]  
(1)

The covariance and ACF of the MA process can be derived from the multiplication of equation (1) by \( y_{t-k} \) to get the following equation:
\[ y_{t-k} y_t = (e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_3 e_{t-3} + \ldots + \theta_q e_{t-q}) (e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_3 e_{t-3} + \ldots + \theta_q e_{t-q}) \]

Taking expected values for both sides, we get:
\[ \gamma_k = E[(e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_3 e_{t-3} + \ldots + \theta_q e_{t-q})(e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_3 e_{t-3} + \ldots + \theta_q e_{t-q})] \]

For covariance with lag 0 (\( k = 0 \)), the \( \gamma_0 \) will be the following:
\[ \gamma_0 = E(e_t e_t) + \theta_1 E(e_{t-1} e_t) + \theta_2 E(e_{t-2} e_t) + \ldots + \theta_q E(e_{t-q} e_t) = \sigma^2 (1 + \theta_1 + \theta_2^2 + \ldots + \theta_q^2) \]

Since the \( E(e_t e_{t-1}) = 0 \) for \( i \neq 0 \) and \( E(e_t e_{t-1}) = \sigma^2 \) for \( i = 0 \), therefore:
\[ \gamma_0 = (1 + \theta_1^2 + \theta_2^2 + \ldots + \theta_q^2) \sigma^2 \]  
(2)

For covariance with lag 1 (\( k = 1 \)), we obtain the following results:
\[ \gamma_1 = E(\theta_1 e_{t-1} e_t + \theta_2 e_{t-2} e_t + \theta_3 e_{t-3} e_t + \ldots + \theta_q e_{t-q} e_t) \]
\[ = \theta_1 \sigma^2 + \theta_2 \sigma^2 + \theta_3 \sigma^2 + \ldots + \theta_q \sigma^2 \]
\[ = (\theta_1 + \theta_2 + \theta_3 + \ldots + \theta_q) \sigma^2 \]
\[ \gamma_k = (\theta_k + \theta_{k+1} + \ldots + \theta_q) \sigma^2 \]  
(3)

From equation (2) and (3), we can calculate the ACF of the MA process.
\[ \rho_k = \frac{\gamma_k}{\gamma_0} = \frac{(\theta_1 \theta_{k-1} + \theta_2 \theta_{k+1} + \ldots + \theta_q \theta_{q+1}) \sigma^2}{(1 + \theta_1^2 + \theta_2^2 + \ldots + \theta_q^2) \sigma^2} \]

MA (1), MA(2) and MA(3) processes can be shown in the following equations:

MA(1): \[ \rho_k = \frac{\theta_1}{1 + \theta_1^2} \]

MA(2): \[ \rho_1 = \frac{\theta_1 + \theta_2}{1 + \theta_1^2 + \theta_2^2} = \frac{\theta_1 (1 + \theta_2)}{1 + \theta_1^2 + \theta_2^2} \]
\[ \rho_2 = \frac{\theta_2}{1 + \theta_1^2 + \theta_2^2} \]

MA(3): \[ \rho_1 = \frac{\theta_1 + \theta_2 + \theta_3}{1 + \theta_1^2 + \theta_2^2 + \theta_3^2} \]
\[ \rho_2 = \frac{\theta_2}{1 + \theta_1^2 + \theta_2^2 + \theta_3^2} \]
\[ \rho_3 = \frac{\theta_3}{1 + \theta_1^2 + \theta_2^2 + \theta_3^2} \]

The value of \( \rho_k \) in the MA(q) process will be zero for \( k > q \)
Appendix 6.8

Autoregressive Moving Average (ARMA) Models

The equation of the models can be written:

\[ y_t = \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \ldots - \theta_q \epsilon_{t-q} \]

To derive the ACF of the ARMA (p,q) models:

Multiply both sides of the equation above by \( y_{t-k} \), to get the following:

\[ y_t y_{t-k} = \phi_1 y_{t-1} y_{t-k} + \ldots + \phi_p y_{t-p} y_{t-k} + \epsilon_t y_{t-k} + \theta_1 \epsilon_{t-1} y_{t-k} + \ldots + \theta_q \epsilon_{t-q} y_{t-k} \]

Taking the expected value of the equation above, we get the following:

\[ \gamma_k = E(\phi_1 y_{t-1} y_{t-k} + \ldots + \phi_p y_{t-p} y_{t-k} + \epsilon_t y_{t-k} + \theta_1 \epsilon_{t-1} y_{t-k} + \ldots + \theta_q \epsilon_{t-q} y_{t-k}) \]

If \( k > q \), the term \( E(\epsilon_t y_{t-k}) = 0 \) and if \( k < q \), the past errors and the \( y_{t-k} \) will be correlated and the autocovariance will be affected by the moving average.

The variance and autocovariance of ARMA(1,1) can be shown in the following equation:

\[ y_t = \phi_1 y_{t-1} + \epsilon_t + \theta \epsilon_{t-1} \]

Multiplying both sides by \( y_{t-k} \), we get the following equation:

\[ y_t y_{t-k} = \phi_1 y_{t-1} y_{t-k} + \epsilon_t y_{t-k} + \theta \epsilon_{t-1} y_{t-k} \]

Taking the expected value of the equation above, we get the following equation:

\[ E(y_t y_{t-k}) = E(\phi_1 y_{t-1} y_{t-k} + \epsilon_t y_{t-k} + \theta \epsilon_{t-1} y_{t-k}) \]

If \( k = 0 \), the equation above will be the following:

\[ \gamma_0 = \phi_1 \gamma_1 + E[(\phi_1 y_{t-1} + \epsilon_t + \theta \epsilon_{t-1})\epsilon_t] + \theta E[(\phi_1 y_{t-1} + \epsilon_t + \theta \epsilon_{t-1})\epsilon_t] \]

\[ = \phi_1 \gamma_1 + E\phi_1 y_{t-1} \epsilon_t + \epsilon_t^2 + E\theta \epsilon_{t-1} \epsilon_t + \theta E(\phi_1 y_{t-1} \epsilon_{t-1} + \epsilon_t \epsilon_{t-1} + \theta \epsilon_{t-1} \epsilon_{t-1}) \]

Since this model assumes that covariance \( y_{t-1} \epsilon_t = 0 \) and \( y_t \epsilon_t = 0 \), therefore:

\[ \gamma_0 = \phi_1 \gamma_1 + \epsilon_t^2 + 0 + 0 + \theta^2 \epsilon_{t-1}^2 \]

\[ = \phi_1 \gamma_1 + \epsilon_t^2 + \theta^2 \epsilon_{t-1}^2 \]

If \( k = 1 \), the covariance can be derived in the following way:

\[ E(y_t y_{t-1}) = E(\phi_1 y_{t-1} y_{t-1} + y_{t-1} \epsilon_t + \theta y_{t-1} \epsilon_{t-1}) \]

\[ \gamma_1 = \phi_1 \gamma_0 + E[(\phi_1 y_{t-2} + \epsilon_{t-1} + \theta \epsilon_{t-2})\epsilon_t] + \theta E[(\phi_1 y_{t-2} + \epsilon_{t-1} + \theta \epsilon_{t-2})\epsilon_{t-1}] \]
\[ \gamma_t = \phi_1 \gamma_{t-1} + \theta_1 \sigma^2_e \]

\[ \gamma_t = \phi_1 \gamma_{t-1} + \theta_1 \sigma^2_e \]

To solve for the autocovariance \( \rho_1 \), we need to rearrange the \( \gamma_0 \) and \( \gamma_1 \) into the following equations:

Recall: \( \gamma_0 = \phi_1 \gamma_1 + \sigma^2_e + \theta_1^2 \sigma^2_e \)

Substitute \( \gamma_1 \) into \( \gamma_0 \) we obtain the following equation:

\[ \gamma_0 = \phi_1 (\gamma_0 + \theta_1 \sigma^2_e) + \sigma^2_e + \theta_1^2 \sigma^2_e \]

\[ \gamma_0 = \phi_1 \gamma_0 + \phi_1 \theta_1 \sigma^2_e + \sigma^2_e + \theta_1^2 \sigma^2_e \]

\[ \gamma_0 - \phi_1 \gamma_0 = \sigma^2_e + \theta_1^2 \sigma^2_e + \phi_1 \theta_1 \sigma^2_e \]

\[ \gamma_0 (1 - \phi_1) = \sigma^2_e + \theta_1^2 \sigma^2_e + \phi_1 \theta_1 \sigma^2_e \]

\[ \gamma_0 = \frac{\sigma^2_e + \theta_1^2 \sigma^2_e + \phi_1 \theta_1 \sigma^2_e}{(1 - \phi_1)} \]

Recall: \( \gamma_1 = \phi_1 \gamma_0 + \theta_1 \sigma^2_e \)

\[ \gamma_1 = \frac{\phi_1 (\sigma^2_e + \theta_1^2 \sigma^2_e + \phi_1 \theta_1 \sigma^2_e) + \theta_1 \sigma^2_e}{(1 - \phi_1)} \]

\[ = \frac{\phi_1 \sigma^2_e + \phi_1 \theta_1 \sigma^2_e + \phi_1 \theta_1 \sigma^2_e + \theta_1 \sigma^2_e}{(1 - \phi_1)} \]

\[ = \left[ \frac{(1 + \phi_1 \theta_1)(\phi_1 + \theta_1)}{(1 - \phi_1^2)} \right] \sigma^2_e \]

\[ \gamma_1 = \left[ \frac{(1 + \phi_1 \theta_1)(\phi_1 + \theta_1)}{(1 - \phi_1^2)} \right] \sigma^2_e \]
Appendices

Appendix 6.9

Lagrange Multiplier (LM) Test

Engle (1982) proposes the use of the Lagrange multiplier test for disturbances using the following steps:

1. Use OLS to estimate the most appropriate AR(n) model:

   \[ y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_n y_{t-n} + \varepsilon_t \]

2. Obtain the squares of the fitted errors \( \hat{\varepsilon}_t^2 \). Regress these squared residuals on a constant and on the “q” lagged values \( \hat{\varepsilon}_{t-1}^2, \hat{\varepsilon}_{t-2}^2, \ldots, \hat{\varepsilon}_{t-q}^2 \)

If there are no ARCH or GARCH effects, the estimated values of \( \alpha_1, \alpha_2, \ldots, \alpha_{t-q} \) will be zero. Hence, this regression will have little explanatory power so the coefficient of determination (i.e. the usual R²-statistic) will be quite low. With a sample of T residuals, under the null hypothesis of no ARCH errors, the test \( T^{R^2} \) converges to a \( \chi^2 \) distribution. If \( T^{R^2} \) is sufficiently large, rejection of the null hypothesis that \( \alpha_1, \alpha_2, \ldots, \alpha_{t-q} \) jointly equal to zero is equivalent to rejecting the null hypothesis of no ARCH errors. On the other hand, if \( T^{R^2} \) is sufficiently low, it is possible to conclude that there are no ARCH effects.
Appendix 6.10
Plot of IDR Estimates Using EWMA with Original Decay Factors
Appendix 6.11
Plot on IDR estimates using EWMA with a Decay Factor of 0.94
Appendix 6.12

Error Estimates of GARCH (one tail at 5% confidence level)

| No | ATS | AUD | BEF | BND | CAD | CHF | DEM | DKK | FFR | GBP | HKD | ITL | JPY | MYR |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
|    | Obs No | Errors | Obs No | Errors | Obs No | Errors | Obs No | Errors | Obs No | Errors | Obs No | Errors | Obs No | Errors | Obs No | Errors |
| 1  | 16   | -0.2 | 106  | -0.01 | 12   | -0.03 | 112  | -0.16 | 74   | -0.16 | 67   | -0.4  | 11   | -0.06 | 12   | -0.11 |
| 2  | 178  | -1.43 | 112  | -0.07 | 174  | -1.53 | 160  | -2.22 | 174  | -0.36 | 174  | -1.25 | 67   | -0.23 | 67   | -0.2  |
| 3  | 232  | -0.2 | 136  | -0.04 | 255  | -0.45 | 174  | -0.79 | 190  | -1.85 | 214  | -0.07 | 173  | -0.82 | 174  | -1.21 |
| 4  | 259  | -0.32 | 145  | -0.77 | 266  | -0.36 | 221  | -2.43 | 204  | -1.43 | 233  | -0.38 | 227  | -0.09 | 255  | -0.47 |
| 5  | 262  | -0.56 | 215  | -0.07 | 271  | -0.05 | 325  | -2.02 | 220  | -4.82 | 263  | -1.84 | 234  | -0.85 | 264  | -0.32 |
| 6  | 294  | -0.28 | 234  | -1.02 | 280  | -0.67 | sum  | -7.62 | 335  | -2.46 | 271  | -0.31 | 255  | -0.25 | 271  | -0.09 |
| 7  | 320  | -0.4 | 258  | -0.22 | 316  | -0.59 | sum  | -1.52 | 350  | -1.52 | 291  | -0.2  | 286  | -0.11 | 280  | -0.59 |
| 8  | 350  | -0.76 | 263  | -0.0 | 327  | -0.65 | sum  | -12.6 | 316  | -0.38 | 268  | -1.2  | 291  | -0.23 | 271  | -0.13 |
| 9  | sum  | -4.12 | 274  | -0.14 | 337  | -0.22 | sum  | -4.83 | 271  | -0.08 | 316  | -0.26 | 280  | -0.47 | 344  | -0.81 |
| 10 | 303  | -0.15 | 350  | -0.36 | 320  | -0.82 | 327  | -0.12 | 291  | -0.09 | sum  | -4.86 | 327  | -0.08 | sum  | -13.2 |
| 11 | 319  | -0.04 | sum  | -4.21 | 316  | -0.15 | sum  | -3.9  | 327  | -0.21 | sum  | -4.05 |
| 12 | 349  | -0.1 | sum  | 2.64  | 327  | -0.21 | sum  | -4.72 |
| 13 | sum  | -0.59 | mean | -0.22 | mean | -0.42 | mean | -1.52 | mean | -1.6 | mean | -0.66 | mean | -0.36 | mean | -0.35 |
| 14 | mean | -0.59 | mean | -0.22 | mean | -0.42 | mean | -1.52 | mean | -1.6 | mean | -0.66 | mean | -0.36 | mean | -0.35 | mean | -0.37 | mean | -0.52 | mean | -0.99 | mean | -1.32 | mean | -0.3 | mean | -0.27 |
## Appendix 6.13

### Test GARCH Residuals

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Appendix 6.14

Correlation Matrices of GARCH Variances

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## Appendix 6.15

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Test using difference p* to obtain evidence for Type II error test:

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<td>0.808</td>
<td>0.808</td>
<td>0.808</td>
<td>0.808</td>
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<td>0.808</td>
<td>0.808</td>
<td>0.808</td>
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</tr>
</tbody>
</table>

TUTF = Time until first failure
## Appendix 6.16

**TUTF Test on EWMA Estimates Based on Original Decay Factors**

<table>
<thead>
<tr>
<th></th>
<th>ATS</th>
<th>AUD</th>
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<th>JPY</th>
<th>MYR</th>
<th>NLG</th>
<th>NZD</th>
<th>SEK</th>
<th>USD</th>
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</thead>
<tbody>
<tr>
<td>N</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>13</td>
<td>73</td>
<td>8</td>
<td>25</td>
<td>8</td>
<td>88</td>
<td>21</td>
<td>38</td>
<td>68</td>
<td>8</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>True $p$</td>
<td>0.200</td>
<td>0.200</td>
<td>0.250</td>
<td>0.077</td>
<td>0.014</td>
<td>0.020</td>
<td>0.125</td>
<td>0.040</td>
<td>0.125</td>
<td>0.011</td>
<td>0.048</td>
<td>0.083</td>
<td>0.026</td>
<td>0.015</td>
<td>0.125</td>
<td>0.200</td>
<td>0.250</td>
<td>0.200</td>
</tr>
<tr>
<td>$p^*$</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
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<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
</tr>
<tr>
<td>LR($N, p^*$)</td>
<td>1.12</td>
<td>1.12</td>
<td>1.32</td>
<td>0.41</td>
<td>0.20</td>
<td>0.02</td>
<td>0.74</td>
<td>0.09</td>
<td>0.74</td>
<td>0.36</td>
<td>0.15</td>
<td>0.46</td>
<td>0.00</td>
<td>0.15</td>
<td>0.74</td>
<td>1.12</td>
<td>1.32</td>
<td>1.12</td>
</tr>
</tbody>
</table>

Accepted / rejected using 5% confidence level*:

- TUFF test using 0.05 type I error
- TUFF test using 0.10 type I error
- Type II error rates using alternative hypothesis (p=0.030)

<table>
<thead>
<tr>
<th></th>
<th>ATS</th>
<th>AUD</th>
<th>BEF</th>
<th>BND</th>
<th>CAD</th>
<th>CHF</th>
<th>DEM</th>
<th>DKK</th>
<th>FFR</th>
<th>GBP</th>
<th>HKD</th>
<th>ITL</th>
<th>JPY</th>
<th>MYR</th>
<th>NLG</th>
<th>NZD</th>
<th>SEK</th>
<th>USD</th>
</tr>
</thead>
</table>
| Test using difference $p^*$ to obtain evidence for Type II error test:  
Let $p^*$ be | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| LR($N, p^*$) | 1.86 | 1.86 | 2.07 | 0.41 | 0.04 | 0.18 | 1.44 | 0.56 | 1.44 | 0.01 | 0.68 | 1.11 | 0.31 | 0.06 | 1.44 | 1.86 | 2.07 | 1.86 |

Type II error rates using alternative hypothesis (p=0.030)

- Type I error rate is the probability of rejecting a true null hypothesis
- Type II error rate is the probability of accepting a false null hypothesis

*) The critical value of the chi-square distribution table is 3.841
### Appendix 6.17

**TUTF Test on GARCH Estimates**

<table>
<thead>
<tr>
<th></th>
<th>ATS</th>
<th>AUD</th>
<th>BEF</th>
<th>BND</th>
<th>CAD</th>
<th>CHF</th>
<th>DEM</th>
<th>DKK</th>
<th>FFR</th>
<th>GBP</th>
<th>HKD</th>
<th>ITL</th>
<th>JPY</th>
<th>MYR</th>
<th>NLG</th>
<th>NZD</th>
<th>SEK</th>
<th>USD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>N</strong></td>
<td>12</td>
<td>106</td>
<td>12</td>
<td>112</td>
<td>74</td>
<td>67</td>
<td>11</td>
<td>12</td>
<td>18</td>
<td>57</td>
<td>112</td>
<td>10</td>
<td>61</td>
<td>28</td>
<td>67</td>
<td>39</td>
<td>16</td>
<td>37</td>
</tr>
<tr>
<td><strong>True p</strong></td>
<td>0.083</td>
<td>0.09</td>
<td>0.083</td>
<td>0.009</td>
<td>0.014</td>
<td>0.015</td>
<td>0.091</td>
<td>0.083</td>
<td>0.056</td>
<td>0.018</td>
<td>0.009</td>
<td>0.010</td>
<td>0.016</td>
<td>0.036</td>
<td>0.015</td>
<td>0.026</td>
<td>0.063</td>
<td>0.027</td>
</tr>
<tr>
<td><strong>p</strong></td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
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<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
</tr>
<tr>
<td><em><em>LR(N,P</em>)</em>*</td>
<td>0.46</td>
<td>0.60</td>
<td>0.46</td>
<td>0.68</td>
<td>0.21</td>
<td>0.14</td>
<td>0.51</td>
<td>0.46</td>
<td>0.22</td>
<td>0.06</td>
<td>0.68</td>
<td>0.58</td>
<td>0.09</td>
<td>0.05</td>
<td>0.14</td>
<td>0.00</td>
<td>0.28</td>
<td>0.00</td>
</tr>
</tbody>
</table>

- **Accepted/Rejected using 5% confidence level**
  - LR(N,P*)
  - TUFF test using 0.05 type I error
  - TUFF test using 0.10 type I error
  - Type II error rates using alternative hypothesis (p=0.030)

Test using difference p* to obtain evidence for Type II error test:

Let p* be

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<thead>
<tr>
<th></th>
<th>ATS</th>
<th>AUD</th>
<th>BEF</th>
<th>BND</th>
<th>CAD</th>
<th>CHF</th>
<th>DEM</th>
<th>DKK</th>
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<th>GBP</th>
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<th>MYR</th>
<th>NLG</th>
<th>NZD</th>
<th>SEK</th>
<th>USD</th>
</tr>
</thead>
<tbody>
<tr>
<td><em><em>LR(N,P</em>)</em>*</td>
<td>1.11</td>
<td>0.00</td>
<td>1.11</td>
<td>0.68</td>
<td>0.04</td>
<td>0.06</td>
<td>1.18</td>
<td>1.11</td>
<td>0.79</td>
<td>0.12</td>
<td>0.01</td>
<td>1.25</td>
<td>0.09</td>
<td>0.49</td>
<td>0.06</td>
<td>0.29</td>
<td>0.88</td>
<td>0.32</td>
</tr>
</tbody>
</table>

- **Type II error rates using alternative hypothesis (p=0.030)**

*) The critical value of the chi-square distribution table is 3.841

Type I error rate is the probability of rejecting a true null hypothesis

Type II error rate is the probability of accepting a false null hypothesis
### Appendix 6.18

**Proportion of Failure Test on EWMA Estimates Based on a 0.94 Decay Factor**

<table>
<thead>
<tr>
<th>T (total observation)</th>
<th>ATS</th>
<th>AUD</th>
<th>BEF</th>
<th>BND</th>
<th>CAD</th>
<th>CHF</th>
<th>DEM</th>
<th>DKK</th>
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<th>GBP</th>
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<th>ITL</th>
<th>JPY</th>
<th>MYR</th>
<th>NLG</th>
<th>NZD</th>
<th>SEK</th>
<th>USD</th>
</tr>
</thead>
<tbody>
<tr>
<td>N (the number of estimation failure)</td>
<td>9</td>
<td>11</td>
<td>12</td>
<td>7</td>
<td>10</td>
<td>14</td>
<td>12</td>
<td>10</td>
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<td>12</td>
<td>10</td>
<td>12</td>
<td>9</td>
<td>12</td>
<td>10</td>
<td>12</td>
<td></td>
</tr>
<tr>
<td>p (the proportion of failure or N/T)</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
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<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>p* (the proportion of failure estimates)</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
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<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
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</tr>
<tr>
<td>LR</td>
<td>0.00</td>
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<td>0.17</td>
<td>0.08</td>
<td>1.19</td>
<td>0.48</td>
<td>0.08</td>
<td>0.00</td>
<td>0.48</td>
<td>0.48</td>
<td>0.08</td>
<td>0.48</td>
<td>0.48</td>
<td>3.35</td>
<td>0.00</td>
<td>0.48</td>
<td></td>
</tr>
<tr>
<td>Chi-square critical value with 5% confidence level is 3.841</td>
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<td></td>
</tr>
</tbody>
</table>

Hypothesis is rejected if LR > 3.841 and accepted if LR < 3.841

The maximum sample size (n) to reject that p=p* with 0.05 confidence level (see Kupiec's Table 4).

<table>
<thead>
<tr>
<th></th>
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<td>0.50</td>
<td>1.31</td>
<td>0.50</td>
<td>1.31</td>
<td>0.50</td>
<td>1.31</td>
<td>0.50</td>
<td>1.82</td>
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<tbody>
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<td>0.92</td>
<td>0.14</td>
<td>0.57</td>
<td>0.14</td>
<td>0.57</td>
<td>0.92</td>
<td>0.14</td>
<td>0.57</td>
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</tbody>
</table>

<table>
<thead>
<tr>
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</thead>
<tbody>
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<td>1.26</td>
<td>0.88</td>
<td>3.69</td>
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<td>0.34</td>
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<td>2.28</td>
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<td>0.89</td>
<td>1.73</td>
<td>0.88</td>
<td>0.01</td>
<td>2.28</td>
<td>0.88</td>
</tr>
</tbody>
</table>
### Appendix 6.19

**Proportion of Failure Test on EWMA Estimates Based on Original Decay Factors**

<table>
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<tr>
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<th>ATS</th>
<th>AUD</th>
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<th>CAD</th>
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<th>JPY</th>
<th>MYR</th>
<th>NLG</th>
<th>NZD</th>
<th>SEK</th>
<th>USD</th>
</tr>
</thead>
<tbody>
<tr>
<td>N (the number of estimation failure)</td>
<td>14</td>
<td>12</td>
<td>14</td>
<td>4</td>
<td>7</td>
<td>12</td>
<td>11</td>
<td>12</td>
<td>13</td>
<td>12</td>
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<td>11</td>
<td>12</td>
<td>12</td>
<td>8</td>
<td>11</td>
<td>10</td>
<td>26</td>
</tr>
<tr>
<td>p (the proportion of failure or N/T)</td>
<td>0.04</td>
<td>0.03</td>
<td>0.04</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.07</td>
</tr>
<tr>
<td>p* (the proportion of failure estimates)</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
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<td>0.03</td>
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<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.07</td>
</tr>
<tr>
<td>LR</td>
<td>1.19</td>
<td>0.48</td>
<td>1.19</td>
<td>1.43</td>
<td>0.17</td>
<td>0.48</td>
<td>0.24</td>
<td>0.48</td>
<td>0.80</td>
<td>0.48</td>
<td>0.48</td>
<td>0.24</td>
<td>0.48</td>
<td>0.48</td>
<td>0.24</td>
<td>0.48</td>
<td>0.08</td>
<td>10.0</td>
</tr>
</tbody>
</table>

Chi-square critical value with 5% confidence level is 3.841

Hypothesis is rejected if LR > 3.841 and accepted if LR < 3.841

The maximum sample size (n) to reject that p = p* with 0.05 confidence level (see Kupiec's Table 4).

- Test hypothesis that the p* is 0.010
  - LR: 7.88 5.55 7.88 0.03 1.19 5.55 4.5 5.55 6.68 5.55 5.55 4.5 5.55 5.55 1.86 4.5 3.53 26.4
- Test hypothesis that the p* is 0.020
  - LR: 2.41 1.31 2.41 0.67 0.00 1.31 0.86 1.31 1.82 1.31 1.31 0.86 1.31 0.86 0.50 13.6
- Test hypothesis that the p* is 0.030
  - LR: 0.47 0.09 0.47 2.35 0.59 0.09 0.01 0.09 0.25 0.09 0.09 0.01 0.09 0.09 0.29 0.01 0.01 7.33
- Test hypothesis that the p* is 0.040
  - LR: 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04 0.04
- Test hypothesis that the p* is 0.05
  - LR: 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05

The table shows the results of applying the proportion of failure test on EWMA estimates based on original decay factors. The test is used to determine if the observed failure rate deviates significantly from a hypothesized rate.

IX-39
### Appendix 6.20

Proportion of Failure Test on GARCH Estimates

<table>
<thead>
<tr>
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<th>CHF</th>
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<th>ITL</th>
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<th>MYR</th>
<th>NLG</th>
<th>NZD</th>
<th>SEK</th>
<th>USD</th>
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<tbody>
<tr>
<td><strong>N (the number of estimation failure)</strong></td>
<td>8</td>
<td>12</td>
<td>10</td>
<td>5</td>
<td>7</td>
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<td>8</td>
<td>11</td>
<td>12</td>
<td>10</td>
<td>6</td>
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<tr>
<td><strong>p (the proportion of failure or N/T)</strong></td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
<td>0.01</td>
<td>0.02</td>
<td>0.02</td>
<td>0.04</td>
<td>0.03</td>
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<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td><em><em>p</em> (the proportion of failure estimates)</em>*</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
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<td>0.03</td>
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</tr>
<tr>
<td><strong>LR</strong></td>
<td>0.03</td>
<td>0.48</td>
<td>0.08</td>
<td>0.84</td>
<td>0.17</td>
<td>0.03</td>
<td>0.80</td>
<td>0.24</td>
<td>0.24</td>
<td>0.00</td>
<td>2.25</td>
<td>0.08</td>
<td>0.03</td>
<td>0.34</td>
<td>0.24</td>
<td>0.48</td>
<td>0.08</td>
<td>0.43</td>
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<tr>
<td><strong>Chi-square critical value with 5% confidence level is 3.841</strong></td>
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</table>

Hypothesis is rejected if LR>3.841 and accepted if LR<3.841

The maximum sample size (n) to reject that p=p* with 0.05 confidence level (see Kupiec's Table 4).

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<td>0.01</td>
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<tr>
<td><em><em>Test hypothesis that the p</em> is 0.020</em>*</td>
<td>1.86</td>
<td>5.55</td>
<td>3.53</td>
<td>0.25</td>
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<td>4.5</td>
<td>2.64</td>
<td>0.03</td>
<td>3.53</td>
<td>1.86</td>
<td>1.86</td>
<td>4.5</td>
<td>5.55</td>
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<tr>
<td>LR</td>
<td>0.06</td>
<td>1.31</td>
<td>0.50</td>
<td>0.28</td>
<td>0.00</td>
<td>0.06</td>
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<td>0.86</td>
<td>0.86</td>
<td>0.23</td>
<td>1.29</td>
<td>0.50</td>
<td>0.06</td>
<td>0.86</td>
<td>1.31</td>
<td>0.50</td>
<td>0.07</td>
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<td><em><em>Test hypothesis that the p</em> is 0.030</em>*</td>
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</tr>
<tr>
<td>LR</td>
<td>0.29</td>
<td>0.09</td>
<td>0.01</td>
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<td>0.01</td>
<td>0.10</td>
<td>3.32</td>
<td>0.01</td>
<td>0.29</td>
<td>0.09</td>
<td>0.01</td>
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<td><em><em>Test hypothesis that the p</em> is 0.040</em>*</td>
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<tr>
<td>LR</td>
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<td>0.14</td>
<td>0.57</td>
<td>3.45</td>
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<td>0.31</td>
<td>0.92</td>
<td>5.70</td>
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<td>0.14</td>
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<tr>
<td>LR</td>
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<td>1.73</td>
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<td>3.69</td>
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<td>1.26</td>
<td>2.28</td>
<td>8.27</td>
<td>1.73</td>
<td>2.93</td>
<td>2.93</td>
<td>1.26</td>
<td>0.88</td>
<td>1.73</td>
<td>4.58</td>
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</table>
Appendices

Appendix 6.21
Kupiec’s Table

Table 1
Critical values for the TUFF test

<table>
<thead>
<tr>
<th>Null Hypothesis probability p*</th>
<th>Non-rejection region for t 0.05 Type I error</th>
<th>Non-rejection for t 0.10 Type I error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.005</td>
<td>11&lt;t&lt;879</td>
<td>21&lt;t&lt;729</td>
</tr>
<tr>
<td>0.010</td>
<td>6&lt;t&lt;439</td>
<td>10&lt;t&lt;364</td>
</tr>
<tr>
<td>0.015</td>
<td>4&lt;t&lt;292</td>
<td>7&lt;t&lt;242</td>
</tr>
<tr>
<td>0.020</td>
<td>3&lt;t&lt;219</td>
<td>5&lt;t&lt;182</td>
</tr>
<tr>
<td>0.025</td>
<td>2&lt;t&lt;175</td>
<td>4&lt;t&lt;145</td>
</tr>
<tr>
<td>0.030</td>
<td>2&lt;t&lt;146</td>
<td>3&lt;t&lt;121</td>
</tr>
<tr>
<td>0.035</td>
<td>2&lt;t&lt;125</td>
<td>3&lt;t&lt;103</td>
</tr>
<tr>
<td>0.040</td>
<td>1&lt;t&lt;109</td>
<td>3&lt;t&lt;90</td>
</tr>
<tr>
<td>0.045</td>
<td>1&lt;t&lt;97</td>
<td>2&lt;t&lt;80</td>
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<tr>
<td>0.050</td>
<td>t&lt;87</td>
<td>2&lt;t&lt;72</td>
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</tbody>
</table>

Table 2
Selected Type II error rates for the TUFF (0.05) test

<table>
<thead>
<tr>
<th>Null hypothesis probability p*</th>
<th>Alternative hypothesis</th>
<th>Type II error rate</th>
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<td>p*=0.010</td>
<td>p=0.015</td>
<td>0.898</td>
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<tr>
<td>p*=0.010</td>
<td>p=0.020</td>
<td>0.868</td>
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<tr>
<td>p*=0.010</td>
<td>p=0.030</td>
<td>0.808</td>
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<tr>
<td>p*=0.010</td>
<td>p=0.040</td>
<td>0.751</td>
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<td>p*=0.010</td>
<td>p=0.050</td>
<td>0.698</td>
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<tr>
<td>p*=0.025</td>
<td>p=0.030</td>
<td>0.908</td>
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<tr>
<td>p*=0.025</td>
<td>p=0.040</td>
<td>0.884</td>
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<tr>
<td>p*=0.025</td>
<td>p=0.050</td>
<td>0.857</td>
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</table>

Table 4
Maximum sample size (T) for which the null hypothesis p=p* is rejected by PF (0.05) test

<table>
<thead>
<tr>
<th>Number of failures</th>
<th>p*=0.01</th>
<th>p*=0.02</th>
<th>p*=0.03</th>
<th>p*=0.04</th>
<th>p*=0.05</th>
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<td>N=1</td>
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<td>3</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<tr>
<td>N=2</td>
<td>34</td>
<td>17</td>
<td>11</td>
<td>9</td>
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<tr>
<td>N=3</td>
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<td>19</td>
<td>16</td>
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<td>N=4</td>
<td>125</td>
<td>63</td>
<td>42</td>
<td>32</td>
<td>26</td>
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<td>N=5</td>
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<td>61</td>
<td>46</td>
<td>37</td>
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<tr>
<td>N=6</td>
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<td>121</td>
<td>81</td>
<td>61</td>
<td>49</td>
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<td>77</td>
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<td>93</td>
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<td>N=9</td>
<td>434</td>
<td>218</td>
<td>146</td>
<td>110</td>
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<td>N=10</td>
<td>503</td>
<td>253</td>
<td>169</td>
<td>127</td>
<td>102</td>
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</table>

Notes:
1. t is the number of observations until the first failure is recorded.
2. The type II error rate is the probability of accepting the false null hypothesis using a 5% confidence level TUFF test when the specific alternative hypothesis is true.
3. Example for Table 4: if two failures are observed in a sample size which employs 34 observations or less, the null hypothesis p*=0.01 can be rejected at the 5% confidence level.
## Appendix 6.22
List of Currencies

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<th>Currencies</th>
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<tr>
<td>AUD</td>
<td>Australian dollar</td>
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<tr>
<td>BEF</td>
<td>Belgian franc</td>
</tr>
<tr>
<td>BND</td>
<td>Brunai Darussalam dollar</td>
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<tr>
<td>CAD</td>
<td>Canadian dollar</td>
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<td>CHF</td>
<td>Swiss franc</td>
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<td>Danish krone</td>
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<td>French franc</td>
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<td>GBP</td>
<td>Great Britain Pound Sterling</td>
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<td>Hong Kong dollar</td>
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<td>Indonesian rupiah</td>
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<td>ITL</td>
<td>Italian lira</td>
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<td>JPY</td>
<td>Japanese yen</td>
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<td>NZD</td>
<td>New Zealand dollar</td>
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<td>SEK</td>
<td>Swedish krona</td>
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<tr>
<td>USD</td>
<td>U.S dollar</td>
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