CHAPTER 3

METHODOLOGY

3.1 Data

This study uses the data of the price series for a sample of finance stocks listed on the Main Board of KLSE. Fifteen counters have been selected randomly as the sample of study, and these stocks are listed in Table 3.1. A simple random selection method is used. First, all the finance stocks in the Main Board of KLSE are numbered, and then fifteen random numbers in the relevant range are generated using the computer. The stocks with numbers corresponding to these generated by the computer are selected into the sample. The period of study is from 1 April 1994 to 30 November 2000.

Table 3.1 The Sample of Finance Stocks Selected for the Study

Stocks	**Name of Companies**
AMMB	AMMB HOLDINGS BERHAD
APEX	APEX EQUITY HOLDINGS BERHAD
COMMERZ	COMMERCE ASSET-HOLDINGS BERHAD
HANCOCK	JOHN HANCOCK LIFE INSURANCE (M) BERHAD
IDRIS	IDRIS HYDRAULIC (MALAYSIA) BERHAD
MAA	MAA HOLDINGS BERHAD
MAYBANK	MALAYAN BANKING BERHAD
MBSB	MALAYSIA BUILDING SOCIETY BERHAD
MGIC	MALAYSIAN GENERAL INVESTMENT CORPORATION BERHAD
MIDF	MALAYSIAN INDUSTRIAL DEVELOPMENT FINANCE BERHAD
OSK	O.S.K. HOLDINGS BERHAD
PBFIN	PUBLIC FINANCE BERHAD
PHILEO	PHILEO ALLIED BERHAD
RHBCAP	RHB CAPITAL BERHAD
TA	TA ENTERPRISE BERHAD

Source: Monthly Statistical Bulletin, Bank Negara Malaysia

There are 63 finance stocks listed on the Main Board of KLSE. The sample used in this study is 24% of the total number of finance stocks. Table 3.2 shows the paid-up capital in Ringgit Malaysia (RM) of each individual stock selected in this study. At November 2000, the total paid-up capital of all finance stocks of the Main Board is RM28,384,376 million. The percentage of the paid-up capital of the selected 15 stocks over the total paid-up capital of all finance stocks is 36%.

Table 3.2 Paid-Up Capital of the Selected Sample Stocks (as at November 2000)

Stocks	**Paid-up Capital (RM'000)**
AMMB	891,599
APEX	213,563
COMMERZ	1,161,617
HANCOCK	100,721
IDRIS	279,984
MAA	111,935
MAYBANK	2,345,675
MBSB	63,888
MGIC	64,456
MIDF	635,520
OSK	531,085
PBFIN	330,000
PHILEO	374,802
RHBCAP	1,823,466
TA	1,328,474
Total (15 stocks)	**10,256,785**

Source: Monthly Statistical Bulletin, Bank Negara Malaysia

Every observation of the daily price series of each individual stock needs to be paired against the KLSE CI series. All the daily closing prices of each individual stock are checked to ensure that returns are calculated only if trading took place. The returns are not calculated for the days where there were no tradings for the particular stock. For a stock, the market returns are computed only if there is a valid observation for this stock on the trading day. This tedious procedure is repeated for each individual stock for every daily closing price. Due to this, only a manageable number of sample stocks are selected in this study.

The daily closing prices are used in this study. The price series of the stocks are collected from the internet, newspaper, Daily Diary published by KLSE and Investors' Digest. The KLSE CI is used as the benchmark market index. The price series are adjusted for capital changes due to bonus issue, rights issue, stock split or consolidation. The measure of daily stock returns is as below:

$$R_{it} = \left(\frac{P_{it} - P_{i,t-1}}{P_{i,t-1}} \right) \times 100 \qquad (3.1)$$

where P_{it} indicates the closing price of stock i, i = 1, 2, ..., 15.

The price of a share relates to market capitalisation and the number of shares that have been issued. Companies can increase or decrease the number of shares issued depending on the situation of the companies. The announcement of rights issues, bonus issues, share splits or consolidation will affect the market capitalisation of the company. The capital changes also have direct effects on the market price of the shares. Hence, price adjustment is needed for the capital changes. The adjustment factors are used to adjust the historical price series before the ex-date of the capital changes.

3.2 Methodology

This study applies an approach that uses two empirical specifications, namely, the quadratic regression technique and the 'dual-beta' model. In addition, some specification tests suggested by Jagannathan and Korajczyk (1986) are also used in this study.

3.2.1 Capital Asset Pricing Model and Beta Coefficients

The Capital Asset Pricing Model (CAPM) describes the relationship between risk and expected return. It serves as a model for the pricing of risky securities. CAPM says that the expected return of a security or a portfolio equals the rate on a risk-free security plus a risk premium. If this expected return does not meet or beat the required return then the investment should not be undertaken.

The applicability of CAPM and knowledge of risk-return relationship are important to the portfolio management. CAPM market line may serve as the benchmark for performance measurement, while the risk-return trade-off line can provide information regarding performance. The basic form of the CAPM may be expressed as follows:

$$E(R_i) = R_F + \beta_i [E(R_M) - R_F] \qquad (3.2)$$

where $E(R_i)$ is the expected return on stock i,

R_F is the return on a risk-free asset,

$E(R_M)$ is the expected return on market, and

β_i is beta coefficient of stock *i*.

There are three testable implications to equation (3.2):

(1) The linear relationship between expected return and the systematic risk of a portfolio.

(2) Managers or investors in the risk-averse market, perceive that portfolio with higher risk should be associated with higher expected return. The condition for the hypothesis is a positive relationship between expected rate of return and systematic risk as measured by the beta coefficient.

(3) For an efficient portfolio, the systematic risk is measured by the beta coefficient (β_i) in equation (3.2). The beta coefficient is a complete measure of the risk of stock *i* since there is no other measurement of risk in equation (3.2). The hypothesis has the condition of no added return for bearing unsystematic risk as measured by the residual variance.

The relationship between the return of a stock and the return on the market is a risk measure. Beta coefficient is a means for measuring the return movements of a security or portfolio of securities in comparison with the market as a whole. This implies that the beta coefficient measures the sensitivity of a stock to market movements. The changes in return on a stock due to factors that affect specifically the price changes of the stock, but not due to factors associated to the market are reflected in the unsystematic risk.

Many professionals and investors use beta to compare a stock's market risk to that of other stocks and the market as a whole. A beta of 1 indicates that the security's expected return will move in random with the market. A beta greater than 1 indicates that the return movements of the security will be more volatile than the market. A beta less than 1 means that it will be less volatile than the market.

3.2.2 Standard Excess Returns Market Model

The standard excess returns market model is as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + e_{it} \qquad (3.3)$$

where R_{it} is the return on stock *i* in day *t*,

α_i is a measure of the abnormal performance of stock *i*,

β_i is a measure of the systematic risk for stock *i*,

R_{mt} is the return on a benchmark market index, and

e_{it} is the error term.

The starting point of the analysis in this study is to use the standard excess returns market model. The excess return is the raw return less the risk-free rate. This linear market model assumes that stocks have no market timing ability, that is, stock returns behaviour is according to CAPM, and investors do not have the macroforecasting skills to decide whether to be in or out of the stock market. We can alter the specification to allow for market timing ability in two different ways.

Referring to the methods that have been used in examination of the selectivity and market timing performance by Fletcher (1995), we utilise a generalised model which is called the quadratic market model, an approach suggested by Chen and Stockum (1985). Furthermore, the analysis includes the dual-beta market model specification of Henriksson and Merton (1981). The two methods are further discussed in the next section. We can see some major differences of the two models in the measurement of stock selection ability and the market timing ability.

3.2.3 Quadratic Returns Market Model

In the quadratic returns market model, the returns on stock *i* is dependent on the quadratic return on a benchmark market index. The quadratic version of the excess returns market model of Chen and Stockum (1985) is as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{mt}^2 + e_{it} \qquad (3.4)$$

where α_i is a measure of the selection ability of stock *i*,

γ_i is a measure of the market timing ability,

and all other variables are as defined above.

A positive gamma ($\gamma_i > 0$) is consistent with a superior or a better market timing ability, whereas a negative gamma ($\gamma_i < 0$) means choosing a stock with 'wrong' timing or perverse market timing ability. When the implied time-varying beta ($\beta_{it} = \beta_i + \gamma_i R_{mt}$) is isolated from the quadratic market model, the following can be seen:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{mt}^2 + e_{it} \qquad (3.4)$$

$$= \alpha_i + (\beta_i + \gamma_i R_{mt})\, R_{mt} + e_{it} \qquad (3.5)$$

If there is a positive relationship between the time-varying beta and the excess return of the stock, a positive value of γ will be found. Hence, higher excess market returns will be implied by a higher market exposure when the market returns are positive. Similarly, a lower market exposure is associated with lower excess returns when market returns are negative. This suggests good market timing ability.

3.2.4 Dual-beta Market Model

The dual-beta excess returns market model suggested by Henriksson and Merton (1981) is as follows:

$$R_{it} = \alpha_i + \beta_{1i}R_{mt} + \beta_{2i}D_tR_{mt} + e_{it} \qquad (3.6)$$

where D_t is a dummy variable which takes a value of negative unity for trading days in which R_{mt} is negative and a value of zero otherwise

and all other variables are as defined above.

The α_i coefficient in equation (3.6) is a measure of the selection ability of the stock and the β_{2i} term is an indication of the market timing ability of the stock. A positive value of β_{2i} is consistent with a superior or better market timing ability. Using the same argument before, the time-varying beta ($\beta_{it} = \beta_{1i} + \beta_{2i}D_t$) can be isolated and equation (3.6) can be written as:

$$R_{it} = \alpha_i + (\beta_{1i} + \beta_{2i}D_t)R_{mt} + e_{it}$$

Thus, a positive β_{2i} suggests good market timing ability as market exposure is reduced when market returns are negative.

3.2.5 Specification Tests

Jagannathan and Korajczyk (1986) suggested exclusion restrictions specification tests for the market timing models. They proposed that the quadratic market model be augmented by a cubic term as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{mt}^2 + \delta_i R_{mt}^3 + e_{it} \qquad (3.7)$$

If the market-timing model is appropriate, then the additional variable should not have significant coefficient. This means that δ_i is not significant. For this reason, the test is also known as exclusion restriction test.

The suggestion for the 'dual-beta' market model specification by Jagannathan and Korajczyk (1986) is to augment with a quadratic term as below:

$$R_{it} = \alpha_i + \beta_{1i} R_{mt} + \beta_{2i} D R_{mt} + \delta_i R_{mt}^2 + e_{it} \qquad (3.8)$$

If the market timing model is appropriate, then δ_i should not be significant. This again is another exclusion restriction test.

3.3 Autoregressive Conditional Heteroscedasticity Models

Researchers engaged in forecasting financial time series, such as stock prices, interest rates and foreign exchange rates have observed that their ability to forecast such variables varies considerably from one time period to another. For example, Mandelbrot (1963) studied the variation of forecasts for speculative prices. This may be due to time-varying behaviour in the volatility of asset prices. Autoregressive Condititional Heteroscedasticity (ARCH) is useful when modeling the conditional variance, or volatility, of a variable.

There are several reasons to model volatility. First, to analyze the risk of holding an asset or the value of an option. Second, to obtain more accurate intervals by modeling the variance of the errors since forecast confidence intervals may be time-varying. Third, to obtain more efficient estimators of a model if heteroskedasticity in the errors can be handled properly.

ARCH models are specifically designed for modelling the variance of the dependent variable as a function of past volatility of the dependent variable. The ARCH models are introduced and developed by Engle (1982) and generalized as GARCH (Generalized ARCH) by Bollerslev (1986).

These models are widely used in various branches of econometrics, especially in financial time series analysis. For example, studies that used these models are included in the recent surveys by Bollerslev, Chou and Kroner (1992), and Bollerslev, Engle and Nelson (1994). Besides that, Baillie and Bollerslev (1989), Bollerslev and Ghysels (1996), Bollerslev and Wooldridge (1992), Judge, Griffiths, Hill, Lutkepohl, and Lee (1985), McCullough and Renfro (1999), McCullough and Vinod (1999), and Weiss (1986) have deliberated on the models and their development.

In developing an ARCH model to model volatility, there are two distinct specifications to be considered which are conditional mean and conditional variance. Investors are only interested to predict the rate of return and risk for the holding period. Therefore, conditional forecasts are more relevant in this case.

For the processes in equations (3.3), (3.4), (3.6), (3.7) and (3.8), a GARCH (p, q) model is

$$e_{it} = v_{it}\sqrt{h_{it}} \qquad (3.9)$$

where $\{v_{it}\}$ is an independently distributed Gaussian random sequence with zero mean and unit variance; h_t is the variance conditional on all the information up to time t – 1, $I_{i,t-1}$ or:

$$h_{it} = a_0 + \sum_{j=1}^{q} a_{1j} e_{i,t-j}^2 + \sum_{j=1}^{p} a_{2j} h_{i,t-j} \qquad (3.10)$$

When p = 0, we have an ARCH(q) model.

The literature review in Chapter 2 shows that ARCH effect is not taken into account in the studies of market timing performance. This study takes a new initiative to investigate the market timing performance without ignoring the ARCH effect. The presence of ARCH effect is examined for equations (3.3), (3.4), (3.6), (3.7) and (3.8). This is important to model the structure of the variance process. The ARCH LM test is performed on all these models used for analysis:

(I) $R_{it} = \alpha_i + \beta_i R_{mt} + e_{it}$ (3.3)

(II) $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{mt}^2 + e_{it}$ (3.4)

(III) $R_{it} = \alpha_i + \beta_{1i} R_{mt} + \beta_{2i} D R_{mt} + e_{it}$ (3.6)

(IV) $R_{it} = \alpha_i + \beta_i R_{mt} + \gamma_i R_{mt}^2 + \delta_i R_{mt}^3 + e_{it}$ (3.7)

(V) $R_{it} = \alpha_i + \beta_{1i} R_{mt} + \beta_{2i} D R_{mt} + \delta_i R_{mt}^2 + e_{it}$ (3.8)

If ARCH effect is found, these equations are to be reestimated to incorporate this effect. The model we suggest to use for the error variance process is as given in equation (3.10).

The Lagrange multiplier (LM) test is commonly used to test for the existence of ARCH in a model of order q. The null hypothesis is no ARCH effect is present, that is, $a_{11} = a_{12} = \ldots = a_{1q} = 0$. To test the existence of ARCH effect, we need to estimate the ARCH(q) model, and obtain the coefficient of determinant, R^2. The test statistic is given by $(n-q)R^2$ where n is the total number of observations. The LM statistic follows a χ^2_q distribution asymptotically under the null hypothesis.