CHAPTER 3

DATA AND METHODOLOGY

3.1 Data

The data used in this study are the daily opening and closing prices, high, low, as well the volume of transactions of 44 stocks traded on the Kuala Lumpur Stock Exchange (KLSE) as well as the Kuala Lumpur Stock Exchange Composite Index (KLSE CI). The stocks are selected randomly from the various Sectors, both from the Main Board and the Second Board. The sample data are from 3 July 1995 to 30 June 2000, a five-year period with a total of 1236 trading days.

The list of 44 stocks, with their respective market capitalisation and other relevant information, namely the Sector, Main or Second Board, is presented as per *Appendix 1*. Of the 44 stocks under study, 33 stocks are traded on the Main Board and 11 are traded on the Second Board. The Sectors involved are the Finance (10), Consumer Products (6), Construction (3), Industrial Products (8), Trading/Services (6), Property (5), Plantation (2), Technology (2) Mining (1) and Hotels (1).

The relevant data on KLSE CI are also collected for the same period. All the data used for the study are sourced from the various commercial databases which contain information on opening and closing prices, high, low, volume of trading, capitalisation, etc., as well as the KLSE Daily Diary and The Star newspaper.

The whole period of the data set is divided into 3 sub-periods to facilitate the analysis of persistency and consistency of market anomaly throughout the different sub-periods, which were under different stock market performance and economic conditions. The first sub-period, which covers 3 July 1995 to 31 July 1997, corresponds with a stable stock market environment and prior to Malaysia being affected by the Asian financial crisis, which started in Thailand in early July 1997. The KLSE CI during this period, a total of 516 trading days, is between 883.96 to 1271.00. The second sub-period refers to 1 August 1997 to 31 August 1998. This period corresponds with the sharp downturn of the Malaysian economy affected by financial crisis, where the KLSE CI declined from 1002.63 to 302.91 within a total of 267 trading days. The third sub-period, from 1 September 1998 to 30 June 2000, corresponds with the implementation of the selective capital controls in Malaysia to contend with the financial crisis. The KLSE CI, with a total of 453 trading days, increased from 262.70, the lowest in the eleven years' history, to 833.37 during this period. The graphical presentation of the KLSE CI from 3 July 1995 to 30 June 2000 is as per *Appendix 2*.

3.2 Methodology

3.2.1 Volatility and Trading Return

The standard deviation of daily stock return is an estimate of the volatility of the stock return. In this study, the volatility of daily stock return is estimated by using the Parkinson (1980) extreme value method, as follows:

$$SD_t = (H_t - L_t)/0.5(H_t + L_t)$$

where SD_t refers to the estimated standard deviation (volatility) of stock on day t

H_t refers to the High price of stock on day t

L_t refers to the Low price of stock on day t

The daily stock trading return is calculated as follows:

$$TR_t = \ln (CP_t/OP_t)$$

where TR_t refers to the trading return of stock on day t

CP_t refers to the Closing Price of stock on day t

OP_t refers to the Opening Price of stock on day t

As the data collected are already adjusted for capital changes such as stock dividend, bonus issues, right issues, stock split and consolidation, no further adjustments of this nature are necessary in the study. Nevertheless, the methodologies for calculating the adjustments for such capital changes are provided as per *Appendix 3* for reference.

3.2.2 Day-Of-The-Week Effect of Volatility and Trading Returns

I. Hypothesis

The null hypotheses tested to determine the existence of the day-of-the-week effect of stock volatility (SD) and trading returns (TR) are as follows:

(a) The mean volatility of each stock on any day is the same across the days of the week; and

(b) The mean trading return of each stock on any day is the same across the days of the week.

The first hypothesis aims to test whether there is any statistically significant difference among the volatilities (SDs) across the days of the week. The null and the alternative hypotheses used in the test for each stock are as below:

$$H_0: \quad SD_{d1} = SD_{d2} = SD_{d3} = SD_{d4} = SD_{d5}$$

$$H_1: \quad \text{At least one pair of } SD_{di} \neq SD_{dj}\text{, where } i \neq j$$

where SD_{d1}, SD_{d2}, SD_{d3}, SD_{d4} and SD_{d5} refer to the standard deviations (volatility) for Monday, Tuesday, Wednesday, Thursday and Friday respectively. If the null hypothesis is rejected at 5% level of significance, this implies that there is a day-of-the-week effect in the stock volatility. Thus, further test such as multiple comparisons test is conducted. The multiple comparisons test is used to determine the pair of days which contributed to the rejection of the null hypothesis of equality of standard deviations.

The second hypothesis is used to test for the presence of statistically significant difference of the trading returns across the days of the week. The null and the alternative hypotheses used in the test for each stock are as below:

$$H_0: \quad TR_{d1} = TR_{d2} = TR_{d3} = TR_{d4} = TR_{d5}$$

$$H_1: \quad \text{At least one pair of } TR_{di} \neq TR_{dj}, \text{ where } i \neq j$$

where TR_{d1}, TR_{d2}, TR_{d3}, TR_{d4} *and* TR_{d5} refer to the trading returns for Monday, Tuesday, Wednesday, Thursday and Friday respectively. If the null hypothesis is rejected at 5% level of significance, this means that there is presence of a day-of-the-week effect in the stock trading returns. Further test such as multiple comparisons test is conducted. The multiple comparisons test is used to determine the pair of days which contributed to the rejection of the null hypothesis of equality of trading returns.

The presence of the seasonal effect, or in this study the day-of-the-week effect, in stock volatility and trading returns will imply that the market is not efficient and investors can use these anomalies to make abnormal profits.

II. One Way Analysis of Variance (ANOVA)

The one-way ANOVA is a statistical method used to decide if the observed differences of means among more than two samples are attributed to chance or the real differences among the population means. In one-way ANOVA, the total variation in the data is sub-divided into that which is attributed to differences among the various groups (or between the treatments) and that which is due to chance or the inherent variation within the various groups (or within the treatments). Within-group variation is considered experimental error while among-group variation is attributable to treatment effects. The null and alternative hypotheses are that the means of the populations under study are equal and that there are some inequalities among these means respectively. Thus, by mathematical presentations, the total variation (i.e. total sum of squares, SST), among-group variation (i.e. sum of squares due to treatments, SST_r) and within-group variation (i.e. sum of squares due to error, SSE) are as follows:

$$SST = SST_r + SSE$$

where $$SST = \sum_{i=1}^{t} \sum_{j=1}^{r_i} (x_{ij} - \bar{x}_{..}{}^2)$$

$$SST_r = \sum_{i=1}^{t} r_i(\bar{x}_{i.} - \bar{x}_{..})^2$$

$$SSE = \sum_{i=1}^{t} \sum_{j=1}^{r_i} (x_{ij} - \bar{x}_{i.})^2$$

where x_{ij} = observation of j^{th} unit receiving i^{th} treatment

$\bar{x}_{..}$ = mean of all observations

$\bar{x}_{i.}$ = mean observation of i^{th} treatment

r_i = number of observations of i^{th} treatment

t = number of treatments

The test statistic of ANOVA is the F-statistic, which is a ratio of the mean square for among-group variation to the mean square for within-group variation or mathematically presented as follows:

$$F = (MST_r)/(MSE) = [SST_r/(t-1)]/[SSE/(N-t)]$$

where t = number of treatments

N = total number of observations

The F-statistic is then compared with the F distribution, with *t-1* and *N-t* degrees of freedom. The null hypothesis will be rejected if the tabulated F-statistic is more than the critical value $F_{\alpha, (t-1), (N-t)}$ at α% level of significance. The rejection of null hypothesis implies that at least a pair of the means is not equal.

In this study, the one-way ANOVA is used separately to test for the equality of volatility (SDs) and trading returns (TRs) across the days of the week. In cases where the null hypothesis is rejected, it implies that there is presence of seasonality or day-of-the-week effect in the volatility or trading returns.

It is important to note that the ANOVA or F-statistic test assumes that the samples are randomly selected from normally distributed populations with equal variances. The ANOVA is, therefore, a parametric test. Thus, normality and equal variances (homoscedasticity) tests are needed before the use of ANOVA in testing the equality of means.

III. Normality Test

A normality test is conducted to justify the normality assumption of the population under study. If the populations are normally distributed, parametric tests such as ANOVA are sufficient to be used in the study. Nevertheless, if the populations are not normally distributed, the alternative test procedures called non-parametric or distribution-free methods are to be used.

In this study, the Kolmogorov-Smirnov (KS) test is used to determine if the populations conform to a normal distribution. The KS test is a test that considers the goodness of fit between a hypothesised distribution function, $F(x)$, and a sample distribution function, $F_n(x)$. The null and alternative hypotheses in the test are as follows:

$$H_o: \quad F_n(x) = F_t(x)$$

$$H_1: \quad F_n(x) \neq F_t(x)$$

The point of greatest divergence between the sample distribution function and the hypotheised distribution function is defined by the following statistic:

$$D_n = max\ |F_n(x) - F_t(x)|$$

where $F_n(x)$ refers to the sample distribution function of a random sample of n observations

$F_t(x)$ refers to the hypothesised distribution function

Based on the above definition, the exact distribution of the statistic D_n can be derived. D_n will tend to be small if the null hypothesis is true and will tend to be larger if $F_n(x)$ is different from $F_t(x)$. The D_n value is compared with the critical value of D_α at the α% level of significance. If the calculated D_n value is greater that the critical value, the null hypothesis will be rejected, implying that the populations are not normally distributed.

IV. Levene Test

The Levene Test is used for testing the equality of the variances across the days of the week for the daily volatility (SDs) and the trading returns (TRs) data under study. It is important to carry out this test since the ANOVA is based on the assumption of equal population variances. The null and alternative hypotheses for this test are as follows:

H_o: $\sigma_1^2 = \sigma_2^2 = \ldots\ldots = \sigma_t^2$

H_1: *At least one pair of the variances is different*

The test statistic is given as follow:

$$F = \frac{[\sum_{i=1}^{t} r_i(\overline{w}_{i.} - \overline{w}_{..})^2]/[t-1]}{[\sum_{i=1}^{t} \sum_{i=1}^{r_i} r_i(w_{ij} - \overline{w}_{j.})^2]/[N-t]} \sim F_{t-1,\, N-t}$$

where $w_{ij} = |x_{ij} - \overline{x}_{i}.|$ is the absolute difference between the jth observation of the unit receiving ith treatment and the sample mean of the ith treatment

$\overline{w}_{i}. = [\sum_{j=1}^{r_i} w_{ij}]/r_i$ is the mean of the absolute differences for the ith treatment

$\overline{w}_{..} = [\sum_{i=1}^{t} \sum_{j=1}^{r_i} w_{ij}]/N$ is the overall mean common to all the absolute differences

N and r_i refer to the total observations and sample size respectively

If the null hypothesis is rejected at the 5% level of significance, the populations are assumed to have unequal variances or heteroscedasticity.

V. *Multiple Comparison Tests*

In the test using ANOVA, the rejection of null hypothesis on equality of mean volatility (SDs) and mean trading returns only provides information that there is inequality of means across the week. It does not indicate the pair of days which has significant statistical difference in mean volatility (SDs) and mean trading returns. Thus, further test such as multiple comparisons test is applied to determine the pair of days which has significant statistical difference in means once the null hypothesis is rejected.

In this study, the Scheffe's test and Bonferroni Multiple Comparison Method, which can be applied to both equal and unequal replications, are used for testing the difference in any pair of mean volatility (SDs) and mean trading returns across the days of the week. These tests compare all the possible pairs of mean volatility (SDs) and mean trading returns to determine if there are significant differences within a pair of means.

(a) *Scheffe's Test*

The Scheffe's test is a method for comparing any and all possible contrasts between treatment means. In this method, the type I error is at most α for any of the possible comparisons. The probability that all possible contrasts among treatment means which can be constructed within a set of interval as given below, is 1 - α :

$$\hat{L} - S\hat{\sigma} \leq L \leq \hat{L} + S\hat{\sigma}$$

where $S^2 = (t\text{-}1)\ F_{\alpha;\, t\text{-}1,}$ *error degrees of freedom* and $\hat{\sigma}_{\hat{L}} = MSE \sum_{i=1}^{t} (c_i^2/r_i)$

For pairwise comparisons, the test hypotheses are as follows:

$H_o: \quad \mu_i = \mu_j \qquad$ vesus $\qquad H_o: \quad \mu_i \neq \mu_j$

The null hypothesis is rejected if $|\bar{x}_{i.} - \bar{x}_{j.}| > S\hat{\sigma}_{\hat{L}}$

or $\quad |\bar{x}_{i.} - \bar{x}_{j.}| > \sqrt{[(t-1)\, F_{\alpha;\, t-1,\, error\, df}]} \times \sqrt{[MSE(1/r_i + 1/r_j)]}$

where $\quad \bar{x}_{i.}$ = mean observation of treatment i

$\bar{x}_{j.}$ = mean observation of treatment j

r_i = sample size of treatment i

r_j = sample size of treatment j

t = number of treatments

If the absolute difference between any pair of days $|\bar{x}_{i.} - \bar{x}_{j.}|$ is significantly greater than $S\hat{\sigma}_{\hat{L}}$, this means that the mean volatility (SDs) and mean trading returns of this pair of days are significantly different.

(b) Bonferroni Test

In this method, the confidence coefficient is at least 1-α that the following coefficient limits for the g contrasts L_i are all correct:

$\hat{L}_i \pm Bs(\hat{L}_i)$, $\qquad i = 1, 2, \ldots, g$

where, $\quad B = t_{\alpha/2g;\, error\, df}$, $\qquad s^2(\hat{L}_i) = MSE \sum_{i=1}^{t} (c_i^2/r_i)$

For all pairwise comparisons, g is equal to ${}^tC_2$.

The test hypotheses are as follows:

$$H_o: \quad \mu_i = \mu_j \qquad \text{vesus} \qquad H_o: \quad \mu i \neq \mu_j$$

The null hypothesis is rejected if

$$/\ \bar{x}_{i.} - \bar{x}_{j.}\ / > t_{\alpha/2g;\ error\ df} \sqrt{\ } [MSE(1/r_i + 1/r_j)]$$

where r_i = sample size of treatment i

r_j = sample size of treatment j

t = number of treatments

The rejection of the null hypothesis implies that the mean volatility (SDs) and mean trading returns of this pair of days are significantly different.

VI. Nonparametric Test

The nonparametric tests should be used if the assumptions of normality and equal variances are not justified. These methods assume no knowledge whatsoever about the underlying populations, except perhaps that they are continuous. The primary disadvantage of nonparametric tests is that they do not utilise all the information provided by the sample, and thus, is less efficient if compared with the parametric methods.

The Kruskal-Wallis (KW) test is one of the nonparametric alternatives to the usual ANOVA for testing the equality of treatment means. The KW test requires the user to first rank the observations in ascending order and replace each observation by its rank, R_{ij}, with the smallest observation having rank 1.

In the case of ties, the average rank to each of the tied observations is assigned to each of the tied observations. The test statistic is given as follows:

$$H = [\frac{12}{N(N-1)} \sum_{i=1}^{t} \frac{R_i^2}{r_i} - 3(N+1)] / [1 - \frac{\sum T}{N^3 - N}] \sim \chi^2_{(t-1)}$$

where R_i = sum of ranks in the i[th] treatment

r_i = number of observations in the i[th] treatment

N = total number of observations

t = number of treatments

T = $m^3 - m$ (where m is the number of tied observations in a tied group)

If the r_i is reasonably large, say equal or more than 5, H is distributed approximately as $\chi^2_{(t-1)}$ under the null hypothesis. Therefore, the null hypothesis is rejected if H value if greater than $\chi^2_{\alpha; (t-1)}$. The rejection of null hypothesis implies that there is at least one pair of the mean across the days of the week which is significantly different.

3.2.3 Granger-Causality of Volatility, Trading Returns and Volume

I. *Hypotheses*

The null hypotheses tested to determine the existence of causal relationship between the stock volatility (SD) and trading return (TR) as well as the stock volatility and trading volume (using ln volume) are as follows:

(a) The stock volatility does not Granger-cause the trading return;

(b) The trading return does not Granger-cause the stock volatility;

(c) The stock volatility does not Granger-cause the trading volume; and

(d) The trading volume does not Granger-cause the stock volatility.

The testing of all the hypotheses above is conducted to determine whether the current value of a variable, say trading return, is explained by the past values of another variable, say stock volatility, apart from the past value of the variable under study (the trading return). The rejection of any of the above hypotheses means that a variable is Granger-caused by another variable. A variable Y is said to be Granger-caused by Z if the lagged values of Z can help to improve the explanation of the current value of Y apart from the past values of Y. Two variables can be independent i.e. no causality; unidirectional causality i.e. one causes the other but not vise versa; or feedback/bidirectional causality relationship i.e. one causes the other and vice versa.

The Granger-Causality (GC) test is used in this study to determine the causal relation between stock volatility and trading return as well as stock volatility and trading volume.

II. Granger-Causality Test

The GC tests investigate the dynamic relationship between two time series. The standard GC tests examine whether the past values in one variable, X, help to explain current values in another variable, Y, over and above the explanation provided by past changes in Y. To determine if causality runs in the other direction, the experiment is repeated by interchanging X and Y. The GC model, for X and Y could be expressed as follows:

$$Y_t = \alpha_{10} + \sum_{i=1}^{m} \alpha_{1i}Y_{t-i} + \sum_{i=1}^{m} \beta_{1i}X_{t-i} + \varepsilon_{1t} \quad \text{...............Model 1}$$

where, ε_{1t} is the white noise, m is the order of the lag for X and Y. From the above model, X is said to Granger-cause Y, if the coefficient, β_{1i} is not equal to zero. Similarly, to determine if Y Granger causes X, the model could be expressed as follows:

$$X_t = \alpha_{20} + \sum_{i=1}^{m} \alpha_{2i}Y_{t-i} + \sum_{i=1}^{m} \beta_{2i}X_{t-i} + \varepsilon_{2t} \quad \text{...............Model 2}$$

From the above model, Y is Granger causing X if coefficient of α_{2i} is not equal to zero.

In generic term, the null and alternate hypotheses to determine the causality between X and Y could be expressed as follows:

H_o : Y does not Granger cause X

H_a : Y Granger causes X

Or H_o : $\alpha_{21} = \alpha_{22} = \ldots = \alpha_{2m} = 0$

H_a : At least one restriction is not true

Models 1 and 2, which are unrestricted models, can be estimated by the Ordinary Least Squares (OLS) method. The restricted model for Y does not Granger cause X that is $\alpha_{2i} = 0$ for i = 1, 2,...., m, is:

$$X_t = \alpha_{20} + \sum_{i=1}^{m} \beta_{2i}X_{t-i} + \varepsilon_{2t}$$

The restricted model can also be estimated using the OLS method. The test statistic for causality is as follows:

$$F = \frac{(RSS_R - RSS_U)/m}{RSS_U/(n-2m-1)}$$

Where RSS_u = Residual Sum of Squares of unrestricted model

RSS_R = Residual Sum of Squares of restricted model

n = Total number of observations

m = Number of lag orders

The null hypothesis is rejected if $F > F_{\alpha;\, m,\, n-2m-1}$; which implies that Y Granger causes X. The process of the above test is repeated for null hypothesis of X does not Granger cause Y; to investigate the presence of reverse direction of causality. The rejection of the null hypothesis implies that a variable Granger causes another variable, and this will contradict the efficient market hypothesis since the investor can use the information to predict the stock price movement.

III. Unit Root Test

It is important to examine the time series for stationarity to avoid the problem of spurious regression due to the usage of non-stationary variables in the regression. A time series is said to be stationary if its means and variance are constant over time and the value of covariance between two time periods depends only on the distance or lag between the two time periods. Thus, a stationary series will tend to return to its mean and fluctuations around this mean will have a broadly constant amplitude.

The unit root test is a test of stationarity. The unit root test could be demonstrated using the following model:

$$Y_t = Y_{t-1} + \varepsilon_t$$

Where ε_t is the stochastic error term that has zero mean, constant variance σ^2 and is not autocorrelated. If the coefficient of Y_{t-1} is equal to 1, it is facing the unit root problem i.e. a non-stationarity situation. The process can also be presented as follows:

$$\Delta Y_t = (\rho - 1)Y_{t-1} + \varepsilon_t \qquad or \qquad \Delta Y_t = \gamma Y_{t-1} + \varepsilon_t$$

If $\rho = 1$ or $\gamma = 0$, Y_t is non-stationary or a random walk. The test hypotheses are as follows:

$$H_o: \quad \gamma = 0 \quad vesus \qquad H_o: \quad \gamma < 0$$

The test statistic is $\tau = \hat{\gamma}$/standard error $(\hat{\gamma})$. The τ resembles a t-statistic but does not follow a t-distribution under H_o because the variance of the process is not constant. The empirical distribution of τ has been tabulated by Dickey and Fuller using the Monte Carlo simulations.

In this study, the Dickey-Fuller (DF) test is used to test for the presence of unit root. The DF test involves the estimation of an autoregressive equation of the following form:

$$\Delta Y_t = \mu + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t$$

The lagged terms ΔY_{t-i} are included to ensure ε_t is not autocorrelated. The number of lagged difference terms to include is determined empirically, with the idea to include enough terms so that the error term is serially independent. The null hypothesis is still $H_0 : \gamma = 0$. When the DF test is applied to this model, it is called augmented Dickey-Fuller (ADF) test. The ADF test statistic has the same asymptotic distribution as the DF statistic and thus, the same critical value can be used.

If the computed absolute value of τ statistic exceeds the DF absolute critical τ value, the null hypothesis is rejected and the series is stationary.

The ADF test is carried out for different lag lengths i.e. from lag 1 to lag 5 to ensure that the outcomes are consistent and the model is robust to different lag lengths.

IV. Vector Autoregressive (VAR) Model

The GC test has only asymptotic validity and is quite sensitive to the lag length assumed. Thus, one of the biggest challenges in conducting the GC test is the ability to incorporate a suitable lag length that will eliminate the autocorrelation in the error terms. If there is presence of autocorrelation in the model, the results of the test may not be accurate. One of the most common methods to determine the optimal lag length, m, is by choosing the value that minimises the Akaike Information Criterion (AIC) or the Bayesian Schwarz Criterion (SIC). The presentation of AIC and SIC are as follows:

$$AIC = n\sum \hat{\mu}_t^2 + 2k$$

$$SIC = n\sum \hat{\mu}_t^2 + k\ ln(n)$$

where $\hat{\mu}$ refers to the residuals and k refers to the number of parameters including intercept. As ln (n) is greater than 2, SIC tends to choose models that are more parsimonious.

In this study, the VAR models are estimated as follows:

$$Y_t = \alpha_{10} + \sum_{i=1}^{m} \alpha_{1i}Y_{t-i} + \sum_{i=1}^{m} \beta_{1i}X_{t-i} + \varepsilon_{1t} \text{ ....Model 1}$$

$$X_t = \alpha_{20} + \sum_{i=1}^{m} \alpha_{2i}Y_{t-i} + \sum_{i=1}^{m} \beta_{2i}X_{t-i} + \varepsilon_{2t} \text{ ....Model 2}$$

By running the VAR models using OLS method for lag 1 to lag 5, the optimal lag length is selected based on the lag length that gives the lowest SIC. Based on the model with the lowest SIC, the coefficient β_{1i} of Model I and coefficient α_{2i} for Model 2 are tested for null hypothesis i.e both are equal to zero.

3.3 Statistical Tools

The statistical tools used in this study are the Excel, SPSS and E-views version 3.0. These computer softwares are used in this study for editing and computing the relevant data as well as for carrying out all the relevant statistical tests.