

CHAPTER 2

Data And Methodology

2.1 DATA

2.1.1 Selection of Data

The data utilised in this study are the daily opening, high, low and closing prices of the Malaysian market; the overall market, both Main Board and Second Board, and various sectors. The sectors include Consumer Products, Industrial Products, Construction, Trading/Services, Industrial, Finance, Properties, Plantation, and Mining. The market capitalisation for the overall market, the 2 boards and the 9 sectors is given in *Appendix I*. The sample data spans from 3 January 1994 to 26 December 2000, covering a period of 7 years with 1725 trading days.

The whole period is divided into 3 sub-periods to enable the analysis of persistency and consistency of market anomaly throughout different market performances & economic conditions. The first sub-period, from 3 January 1994 to 31 July 1997, corresponds with a stable stock market environment. The second sub-period refers to 1 August 1997 to 31 August 1998, the period of sharp decline on the Malaysian economy caused by the Asian financial crisis. The third sub-period covers from 1 September 1998 to 26 December 2000, coinciding with the implementation of selective capital controls in Malaysia to contend with the financial crisis. The trends of all the indices are presented in *Appendix II*.

2.1.2 Sources of Data

The data utilised in this study are obtained from the Daily Diary published by the KLSE. The Investor's Digest provides the information on the market capitalisation for the overall market, the 2 boards and the 9 sectors.

2.2 METHODOLOGY

2.2.1 Trading Return and Volatility

The daily stock returns are computed as follows:

$$TR_t = \log\left(\frac{CP_t}{OP_t}\right) \times 100$$

where TR_t = Trading return for day t

CP_t = Closing index for day t

OP_t = Opening index for day t

As trading return for a particular day is obtained using the opening and closing index of the same day, no data needs to be omitted to control for non-trading days causing day-of-the-week effects.

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:

$$SD_t = \frac{(H_t - L_t)}{0.5(H_t + L_t)}$$

where SD_t = Estimated standard deviation (volatility) of index for day t

H_t = Highest index for day t

L_t = Lowest index for day t

2.2.2 Day-of-the-Week Effects

i) Research Model of Trading Returns and Volatility

The Ordinary Least Square (OLS) regression model, with the assumptions of normality and equal variances, is used as the estimation model for testing whether seasonality exists in the daily mean trading returns and volatility of the indices in this study. In addition to that, the GARCH model is utilised for capturing the time dependence of volatility in the return series.

The Ordinary Least Squares (OLS) method is utilized to regress the returns for each index on the dummy variables:

$$TR_t = \mu_1 D_{1t} + \mu_2 D_{2t} + \mu_3 D_{3t} + \mu_4 D_{4t} + \mu_5 D_{5t} + e_t$$

Where TR_t = Daily trading returns for individual stocks

D_{1t} to D_{5t} = Dummy variables for Monday to Friday

For Monday, $D_{1t} = 1$ and 0 otherwise; and so on.

e_t = Random error term associated with that day

The OLS coefficients, μ_1 to μ_5 are the mean returns for Monday through Friday. The t-statistics for the OLS estimates are computed using Newey-West heteroscedasticity and autocorrelation-consistent estimator of the covariance matrix.

Hypotheses tested:

- (a) There is equality of mean trading returns across the days in the week. Rejection of the null hypothesis would indicate day-of-the-week effect (weekend effect for Monday).
- (b) There is equality of mean stock volatility across the days in the week. Rejection of the null hypothesis would indicate day-of-the-week effect of stock volatility.
- (c) The day-of-the-week effects in the market trading returns are due to seasonal variation in equity market risk.

For (a) and (b):

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ against

$H_a : \text{At least two } \mu \text{ are not equal}$

where $\mu_1, \mu_2, \mu_3, \mu_4, \mu_5 = \text{Mean trading returns/stock volatility for Monday through Friday, respectively.}$

If the null hypothesis is rejected at 1% or 5% level of significance, a further analysis is carried out i.e. a multiple comparison test to identify the pairs of trading days that contribute to the rejection of the null hypothesis.

For (c):

The family of ARCH models is used to estimate simultaneously the conditional mean and variance of the returns on the stocks and also on the market. More specifically, a very general GARCH (p,q)-M model will be used to investigate the seasonal variation of return volatility of each stock,

$$TR_t = \alpha_0 + \alpha_1 h_t^{1/2} + \alpha_2 TR_{t-1} + \sum_{m=1}^d \mu_m \delta_t^m + \xi_t$$

$$h_t = \beta_0 + \sum_{i=1}^q \beta_i \xi_{t-i}^2 + \sum_{j=1}^p \gamma_j h_{t-j} + \sum_{m=1}^d \mu_m^* \delta_t^m$$

where ξ_t is an error term with zero mean and conditional variance h_t ; α_0 and β_0 are constants; α_1 is the reward to risk ratio; α_2 , β_i , γ_j , μ_m and μ_m^* are coefficients; δ_t^m is the set of deterministic daily seasonal dummies; where the order of $p \geq 0$, $q \geq 0$, p is the order of GARCH terms and q is the order of ARCH terms; and

$$\alpha_0 > 0, \beta_i > 0, \quad i = 1, \dots, q;$$

$$\gamma_j > 0, \quad j = 1, \dots, p$$

For $p = 0$, the process reduces to ARCH(q) process. For $p = q = 0$, ξ_t is simply following a white noise process. In the ARCH(q) process the conditional variance is specified as a linear function of the past variances. However, in the GARCH(p, q) process, it allows both time-varying conditional heterocedasticity and conditional variance.

The Schwarz Information Criterion (SIC) will be used to identify the order of p and q in the GARCH model. This information criterion has been widely used in time series analysis to determine the appropriate length of the distributed lag and has the tendency of choosing a parsimonious model. The distributed lag can be determined by selecting the model with the smallest information criterion. To simplify the procedure of the selection of the most appropriate model, the same order is used simultaneously for both ARCH and GARCH. The highest order of lags considered in this study is 5. The SIC is given by:

$$\text{Minimise} \left(\frac{SS_E}{N} \right) N^{k/N}$$

where N = number of observations

k = number of independent variables including constant

SS_E = sum of squares for error

Mean returns on particular days, in the form of daily dummies, that were found to be significant using the OLS method are identified and utilized as a part of the explanatory variables in the GARCH model. If the deterministic daily seasonal dummies remain significant in spite of the inclusion of the ARCH term, $h_t^{1/2}$, in the conditional mean, we can conclude that seasonality in the daily market trading returns is not due to temporal variation in equity market risk as proxied by the ARCH model. Alternatively, if the inclusion of $h_t^{1/2}$ in the conditional mean renders the deterministic dummies in the mean equation insignificant, but significant in the equation for the conditional variance, we can conclude that the seasonality in the returns are due to daily variation in equity market risk.

ii) Normality Test

Many parametric tests require normally distributed variable in order for their results to be valid. In this study, the Kolmogorov-Smirnov (KS) test is used to determine if the population conforms to a normal distribution. The Kolmogorov-Smirnov Z is computed from the largest difference (in absolute value) between the observed and theoretical cumulative distribution functions. In other words, this is a goodness-of-fit

test between a hypothesised distribution function, $F_r(x)$, and a sample distribution function, $F_n(x)$. The null and alternative hypotheses in the test are as follows:

$$H_0: F_n(x) = F_r(x)$$

$$H_a: F_n(x) \neq F_r(x)$$

The largest difference between the two functions is computed as follows:

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

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 large if $F_n(x)$ is different from $F_r(x)$. The D_n value is compared with the critical value of D_α at the $\alpha\%$ level of significance. If the calculated D_n value is greater than the critical value, the null hypothesis will be rejected, implying that the population is not normally distributed.

iii) Levene Test

The Levene test is used to test the null hypothesis that the populations have homogenous variances. Under the classical linear regression model, homoscedasticity (equal variances) is one of the assumptions that must be satisfied in order to obtain valid results for parametric tests. The null and alternative hypotheses are stated below:

$$H_0: \sigma_1^2 = \sigma_2^2 = \dots = \sigma_r^2$$

$$H_a: \sigma_i^2 = \sigma_j^2, \text{ where } i \neq j = 1, 2, \dots, r$$

The test statistic F , distributed with degrees of freedom $(r - 1)$ and $(N - r)$, is given by:

$$F = \frac{\left[\sum_{i=1}^r b_i (\bar{w}_i - \bar{w}_{..})^2 \right] / [r - 1]}{\left[\sum_{i=1}^r \sum_{j=1}^{b_i} (\bar{w}_{ij} - \bar{w}_i)^2 \right] / [N - r]} \sim F_{r-1, N-r} \text{ under } H_0$$

where $w_{ij} = |x_{ij} - \theta_i|$ is the absolute difference between the j^{th} observation of the unit receiving i^{th} treatment and the sample mean of the i^{th} treatment.

$$\bar{w}_i = \frac{\sum_{j=1}^{n_i} w_{ij}}{n_i} \text{ is the mean of the absolute differences for the } i^{\text{th}} \text{ treatment.}$$

$$\bar{w}_{..} = \frac{\sum_{i=1}^r \sum_{j=1}^{n_i} w_{ij}}{N} \text{ is the overall mean common to all the absolute differences.}$$

N and n_i refer to the total number of observations and sample size of the i -th treatment, respectively. If the null hypothesis is rejected at the 5% significance level, the populations are assumed to have unequal variances.

iv) Parametric Tests

The parametric tests used in this study are the t -test for one sample, One-way Analysis of Variance (ANOVA) and the multiple comparison tests which are the Tukey's test and the Scheffe's test.

a) One sample t -test

The one sample t -test is applied to examine the null hypothesis that the mean trading returns from indices are significantly different from zero on a certain day of the week. The null and alternative hypotheses for this test are as follows:

$$H_0: \mu_d = 0$$

$$H_a: \mu_d \neq 0$$

The test statistic with a degree of freedom of (n_i-1) is defined as:

$$t = \frac{\bar{R}_d - 0}{s/\sqrt{n}} \sim t_{(n_i-1)}$$

in which \bar{R}_d refers to the mean trading returns of each index on a given weekday, s refers to the sample standard deviation and n refers to the sample size. The rejection of a null hypothesis shows that the mean trading returns of an index on a certain day of the week is significantly different from zero, thus, indicating the existence of day-of-the-week effect.

b) *One-way Analysis of Variance (ANOVA)*

The One-way ANOVA is used to test the null hypothesis of equal means of trading returns or stock volatility across the trading week. A single-factor, fixed-effects model to compare the effects of one factor on a dependent variable is utilized. Certain assumptions must be satisfied in order for the result to be valid such as samples must be randomly selected from normally distributed populations with equal variances.

The test statistic for One-way ANOVA is the F ratio. This statistic gives the ratio of the mean square for between-groups variance to the mean square for within-group variance:

$$F = \frac{MS_{Treatment}}{MS_E} = \frac{SS_{Treatment} / (r - 1)}{SS_E / (N - r)}$$

where $SS_{Treatment}$ refers to the sum of squares due to treatments (between treatments) and SS_E is the sum of squares due to error (within treatments). r refers to the number of groups and N is the total number of observations.

The F ratio is then compared to the F distribution, with $(r-1)$ and $(N-r)$ degrees of freedom. If the calculated F ratio is greater than the critical value $F_{\alpha,(r-1),(N-r)}$ at $\alpha\%$ significance level, the null hypothesis would be rejected. This means that at least two of the mean daily trading returns or daily stock volatilities are significantly different, proving the existence of the day-of-the-week effects in the market.

c) *Tukey's test*

The Tukey's test is the most powerful when pairwise differences between means are to be examined. In this study, this test is only applied to indices that have significant unequal mean trading returns or stock volatilities across the trading week under the One-way ANOVA for the purpose of identifying pair(s) of mean trading returns or stock volatilities that are different across the days of the week. In this test, comparison of all possible pairs of days with mean trading returns or stock volatility that differ is conducted to determine if there is a significant difference. The Tukey's test procedure is based on the studentized range statistic, where the difference of two means is only significant if the absolute value of their difference exceeds the critical value, T_α . The critical value is given by:

$$T_\alpha = q_{(\alpha,r,v)} \sqrt{\frac{MS_E}{\tilde{n}}}$$

- in which
- $q_{(\alpha,r,v)}$ = critical value of studentized range statistic
 - \tilde{n} = harmonic mean of the sample sizes
 - α = level of significance, 5%
 - r = number of groups
 - v = degrees of freedom for error

If the absolute difference between any pair of days $|\mu_i - \mu_j|$ is significantly greater than the critical value, the mean trading returns or stock volatilities of the particular pair of days are significantly different.

d) *Scheffe's test*

Unlike the Tukey's test, the Scheffe's test is reasonably robust to departure from assumptions of normality and homoscedasticity. This test is also a more appropriate test when the sizes of samples are unequal. The purpose of conducting this test is the same as the Tukey's test which is to identify pairs of days with significant difference in mean returns. As with the Tukey's test, the application of this test is also limited to stocks that presented significant result of having varying means across the week. The procedure of testing is the same as the Tukey's test with the exception of the critical value used. The critical value for this test is:

$$S_{\alpha} = \sqrt{(r-1)F_{\alpha;r-1,N-r}} \sqrt{MS_E \left(\frac{1}{n_i} + \frac{1}{n_j} \right)}$$

- in which
- $F_{\alpha;r-1,N-r}$ = critical value from the F distribution
 - r = number of groups

N	= total number of observations
n_i	= sample size of group i
n_j	= sample size of group j
α	= level of significance, say, 5%

v) Non-parametric Tests

The non-parametric tests are utilized when the assumptions of normality and equal variances are not satisfied. As mentioned earlier, the violation of these assumptions will render the results obtained from parametric tests invalid. In this study, the non-parametric test used for testing the existence of seasonality in the stocks is the Kruskal-Wallis test.

The Kruskal-Wallis test is commonly used as the alternative to the usual F -test in the analysis of variance for testing the existence of the day-of-the-week effect. This test is a distribution-free test which uses ranks based only on assumptions that the samples are continuous and rankable. The null hypothesis is that the mean daily trading returns/ stock volatility of the 5 trading days of the week are equal.

To perform this test, the observations are ranked in ascending order and are replaced by their rank, with the smallest observation having rank 1. The test statistic is given by:

$$H = \frac{12}{N(N-1)} \sum_{i=1}^r \frac{T_i^2}{n_i} - 3(N-1)$$

where T_i = sum of ranks in the i^{th} treatment
 n_i = number of observations in the i^{th} treatment
 N = total number of observations
 r = number of samples which is 5 in this study

In the case of ties where observations share the same value, an average rank is assigned to each of the tied observations. When there are a number of ties, a correction factor will be calculated and used to correct the H value. The correction factor is as follows:

$$C = 1 - \left\{ \frac{\sum_i^M (g_i^3 - g_i)}{N^3 - N} \right\}$$

where M = number of sets of tied observations

g_i = number of ties in any set i

The new H value is given below:

$$H = \frac{\frac{12}{N(N-1)} \sum_{i=1}^r \frac{T_i^2}{n_i} - 3(N-1)}{C}$$

If the null hypothesis is true, and the sample sizes of the r samples are not too small, the test statistic H is distributed approximately as chi-square, χ^2 , with degree of freedom of $(r-1)$. Rejection of the null hypothesis which occurs when the H value is greater than $\chi_{\alpha, r-1}^2$ will indicate that day-of-the-week effects exist in daily trading returns or daily stock volatility of the stocks.

2.2.3 Granger-Causality of Trading Returns and Volatility

i) Hypotheses

In this study, trading returns and market volatility are examined for the existence of causal relationship. The null hypotheses tested are as follows:

- a) The market volatility does not Granger-cause the trading returns, and
- b) The trading returns does not Granger-cause the market volatility

The testing of these hypotheses is conducted to examine whether the current value of a variable is explained by the past values of another variable apart from the past values of the variable under study. The rejection of any of the null hypotheses mentioned above means that a variable is Granger-caused by another variable. For example, trading returns are said to be Granger-caused by volatility if the lagged values of volatility help to improve the explanation of the current value of trading returns, apart from the past values of trading returns itself. Two variables can be independent or no causality, unidirectional causality i.e. one causes the other but not vice versa or 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 relationship between stock volatility and trading returns.

ii) The Unit Root Test of Stationarity

A time series is said to be stationary if its mean and variance are constant over time and the value of covariance between two time periods depends on the distance or lag between the two time periods and not on the actual time at which the covariance is computed. It is important to establish whether the series utilised are stationary before

further tests are performed, as usage of non-stationary series in regression will give spurious results. In this study, the trading returns and market volatility will be subjected to the unit root test to establish the stationarity of these series before further tests are performed to explore the relationship between these two variables.

The unit root test of stationarity can be demonstrated with the following model:

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

where ε_t is the stochastic error term that follows the classical assumptions of having zero mean, constant variance σ^2 and is not autocorrelated. If the coefficient of Y_{t-1} is equal to 1, we would have a unit root problem which indicates a nonstationary situation. The process is often expressed in an alternative form as

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

where $\delta = (\rho-1)$. From here, if $\rho = 1$ or $\delta = 0$, Y_t is non-stationary or follows a random walk. The test hypotheses are as follows:

$$H_0 : \delta = 0 \quad \text{against}$$

$$H_a : \delta < 0$$

Under this null hypothesis, the test statistic is $\tau = \hat{\delta} / \text{standard error}(\hat{\delta})$. The test resembles a t-statistic but does not follow Student's t distribution because the variance of the process is not constant under H_0 . The critical values for the test are tabulated by Dickey and Fuller using the Monte Carlo simulations.

The Dickey-Fuller(ADF) test is utilised to test for the presence of unit root. The DF test involves the estimation of an autoregressive equation in the following form:

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

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 lags so that the error term is not serially correlated. It is to be noted that when these terms are included, this is actually the augmented DF(ADF) test. As the ADF test statistic has the same asymptotic distribution as the DF statistic, the same critical values can be used. For this study, the test is carried out for lag lengths of 1 to 5 to ensure that the model is robust to different lag lengths.

Rejection of the null hypothesis occurs when the computed absolute value of τ statistic exceeds the absolute critical value, implying that the unit root does not exist and, thus, the series is stationary.

iii) Vector Autoregressive (VAR) Model

The VAR models estimated using the OLS are as follows,

$$\text{Model 1: } TR_t = \alpha_{10} + \sum_{i=1}^m \alpha_{1i} TR_{t-i} + \sum_{i=1}^m \beta_{1i} SD_{t-i} + \varepsilon_{1t}$$

$$\text{Model 2: } SD_t = \alpha_{20} + \sum_{i=1}^m \alpha_{2i} TR_{t-i} + \sum_{i=1}^m \beta_{2i} SD_{t-i} + \varepsilon_{2t}$$

where TR and SD are both variables of interest in the study i.e. trading returns and volatility, respectively, ε_{1t} and ε_{2t} are both white noise and m is the order of the lags for both variables. The models are run with lag lengths of 1 to 5. Selection of the optimal lag length is done by choosing the model giving the lowest SIC. A suitable lag length

chosen will eliminate the problem of autocorrelation, which will render results of tests inaccurate, in the model.

Based on the model with the lowest SIC, the coefficient β_{1i} of Model 1 and α_{2i} of Model 2 are tested on whether they are significantly different from zero. The same model is used for the Granger-Causality test.

iv) Granger-Causality(GC) Test

The GC test examines the short-term dynamic relationship between two time series. It investigates whether the past values of one variable i.e. volatility helps to explain the current values in another variable i.e. return, apart from explanation provided by past changes in return itself. To determine whether causality runs in the other direction, the test is repeated by interchanging volatility and returns as in the VAR models shown above. In general, the null and alternative hypotheses are stated below:

H_0 : *TR* does not Granger-cause *SD* against

H_a : *TR* Granger-causes *SD*

Or H_0 : $\alpha_{21} = \alpha_{22} = \dots = \alpha_{2m} = 0$ against

H_a : At least one restriction is not true

Models 1 and 2 (in the VAR section) are unrestricted models. Using the hypotheses above as example, the restricted model for Model 2 is as follows:

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

The restricted model is also estimated using the OLS method. The test statistic for causality is

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

where RSS_U = Residual sum of squares of the unrestricted model,

RSS_R = Residual sum of squares of the restricted model,

N = Total number of observations, and

m = Number of lag orders

The null hypothesis is rejected if $F > F_{\alpha; m, N-2m-1}$ in which it will imply that TR Granger-causes SD. The process is repeated for the null hypothesis of SD does not Granger-cause TR to investigate the presence of reverse direction causality. The findings of causal relationship between variables will contest the notion of market efficiency as the information can be used to predict price movement.

2.3 Statistical Tools

The statistical tools used for computations and performing various statistical tests on the data in this study are Excel, SPSS and Eviews version 3.