CHAPTER FOUR

DATA AND METHODOLOGY

This paper examines three major analyses namely the relationship analysis between selected economic indicators and the Malaysian Stock Index Futures, forecasting technique ability testing for market efficiency using trading rules to produce above-average returns and lastly is the ex-post forecasting technique to reconfirm testing the market efficiency.

Our dependent variable is the Stock Index Futures. The study at first use stepwise regression to analyze various independent variables. Later four economic indicators will be chosen as independent variables in the final regression equation. The sample data used in the regression are monthly data from January 1996 to December 2000 extracted from the Bank Negara Malaysia (BNM) published monthly statistical bulletin, Statistics Department of Malaysia, various local daily newspaper, in particular The New Straits Times and The Star, The KLSE monthly Investor Digest and Malaysia Derivatives Exchange (MDEX) respectively.

4.1 Preliminary Regression- Stepwise Regression

Stepwise regression is a method used to determine the relevant explanatory variables from a set of candidate explanatory variables in which the numbers of explanatory variables are too large to allow all possible regression models to be computed. At the start of the research six variables are used in the equation, namely:

1) Futures Monthly Volume.
2) Kuala Lumpur Stock Exchange Composite Index (KLSE CI).
3) Market Capitalization of the Kuala Lumpur Stock Exchange.
4) Monetary Aggregates represented by M1.
5) Interest Rates in term of saving deposit for commercial banks.
6) Industrial Production Index (IPI), which represents the economic activities.

The stepwise regression technique is used to determine the statistically significant variables. The regression suggested only four indicators should be used, namely:

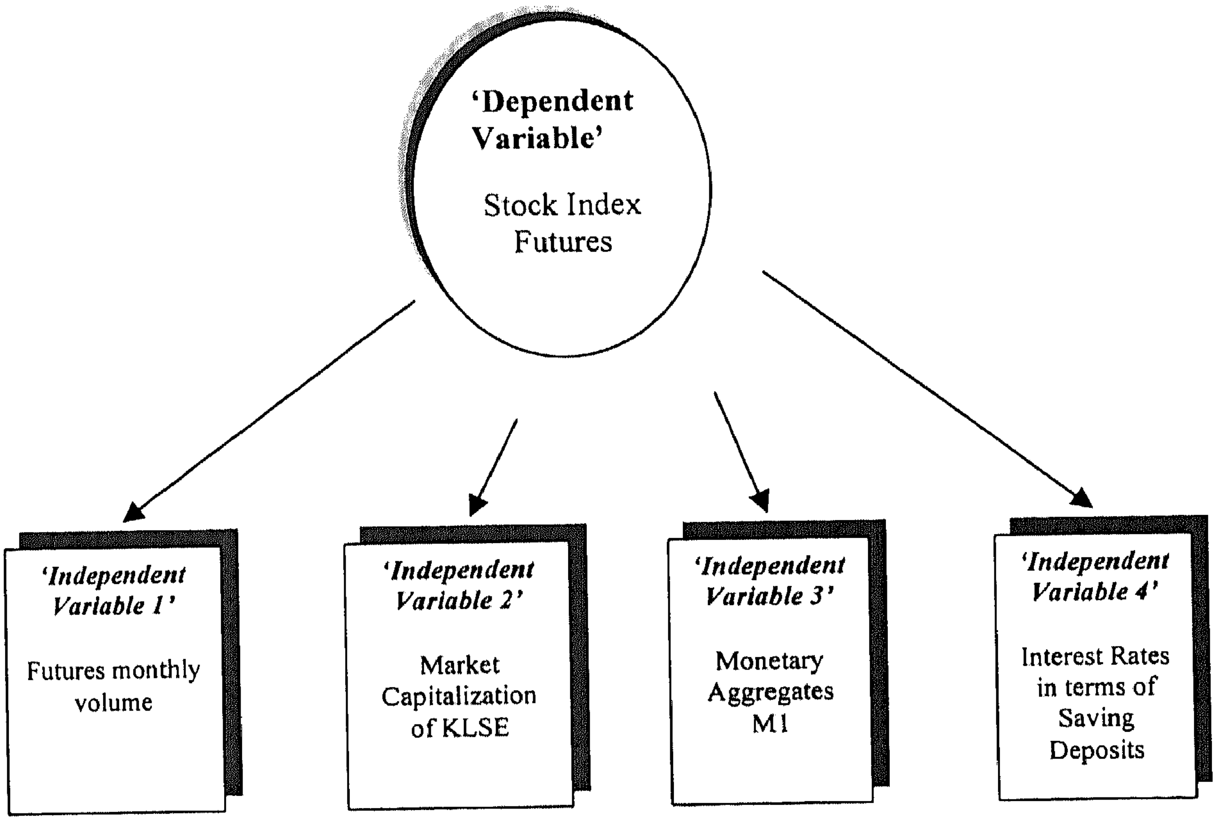
a) Futures Monthly Volume
b) Market Capitalization of the Kuala Lumpur Stock Exchange
c) Monetary Aggregate total M1
d) Interest Rates in saving deposits for commercial banks

The explanatory model for Stock Index Futures (SIF) is the form

SIF = f (futures volume, market capitalization, monetary aggregates (M1), interest rates)

Figure 4.1

Dependent and Independent Variables



* All independent variables are the selected indicators.

The analysis in this paper can be divided into four parts. In the first part, regression analysis using the ordinary least squares (OLS) method is used. Relationship of the selected indicators on stock index futures is tested by slotting in stock index futures as dependent variable whereas KLSE Market Capitalization, Monetary Aggregate (M1), Interest Rates in saving deposit for commercial banks and stock index futures' volume as independent variables.

In the second part, the time-series forecasting methods namely Moving Averages and Single Exponential Smoothing are used to forecast the Stock Index Futures data and completely testing the market efficiency. Then using some trading rules (**buy at the closing price** when we **forecast market up** and **sell at the closing price** when **forecast market down**), we analyze whether we could make above average returns and outperform the stock index futures market.

In the third part is the sample forecasting technique using lags of 1 period (t-1). The t-1 data of the four independent variables to forecast the t-period (current period) data on the Stock Index Futures (the independent variables). Using the same trading rules and assumptions then the weak form market efficiency is tested.

The last part, which is the most important, is the ex-post forecast which we use the first 30 observations to forecast next 30 observations using lag (t-1) model for all the independent variables and use same trading rules and assumptions to ascertain whether the market could be outperformed and if it is not, we can safely confirm that our local Malaysian Stock Index Futures market is a weak form market efficiency.

Sources of Data

This study utilized monthly data of dependent variables and independent variables m:

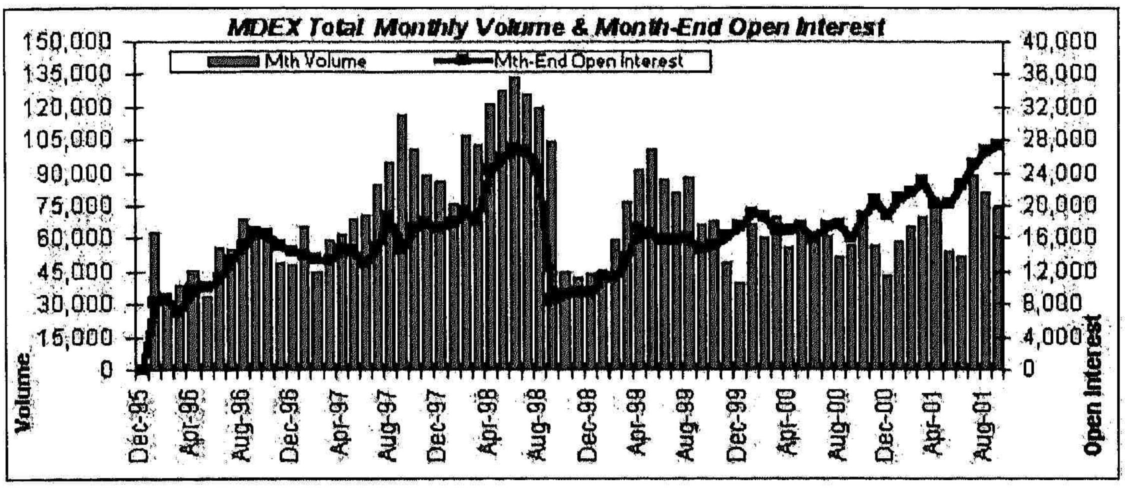
- The Bank Negara (BNM) published its monthly statistical bulletin and covers mainly on monetary indicators for Malaysia.
- Jabatan Perangkaan Malaysia or Statistic Department of Malaysia. The data collection, studies and surveys have traditionally been conducted by Jabatan Perangkaan Malaysia.
- The KLSE monthly Investor Digest.
- Various local daily newspapers, in particular The New Straits Times and The Star.
- Malaysia Derivatives Exchange website at www.mdex.com.

The Selected Economics Indicators

.1) Stock Index Futures' Volume (Monthly)

Futures monthly volume has been calculated by adding each day volume for a nth. Volume has been increasing from the period of 1997-1998, which suggested that futures market experienced its bearish trend and players tend to sell out futures, which icate the high volume traded within the period of time.

Figure 4.2: MDEX Total Monthly Volume



Source: MDEX Website at www.mdex.com

4.3.2) Market Capitalization (RM billions)

As the underlying asset of the Stock Index Futures is the KLSE Composite Index, the inclusion of the Market Capitalization as an independent variable has been considered as excellent economic indicator in determining the relationship of the stock index futures.

A. Capitalization-Weighted

A capitalization-weighted index measures the change in the market value of the index components. In this type of index the sum of all the market values (market value = price x outstanding shares) divided by the index divisor equals the index value.

:xample:

	Outstanding		
Stock	price	shares	market value
A	10.00 x	50.00	= 500.00
B	5.00 x	75.00	= 375.00
C	15.00 x	10.00	= 150.00

1025.00= total market value

3ase Date & Base Value:

'ust like a price-weighted index, a capitalization-weighted index must have a base date ınd a base value. Again, we will use the ABC example.

Divisor:

Example:

	Outstanding		
Stock	price	shares	market value
A	10.00 x	50.00	= 500.00
B	5.00 x	75.00	= 375.00
C	15.00 x	10.00	= 150.00

1025.00= total market value

1025.00 / index divisor = index value

We will set the base value to be equal to 100, so:

Total market value / desired index value = index divisor

1025.00 / 100 = 10.25

In a capitalization-weighted index, the divisor can change very often because of hanges in the market value. Reasons for a divisor change in a capitalization-weighted ıdex are: outstanding share increase or decrease, spin off, and a deletion or addition. 'he reason there is no divisor change for a split in a capitalization-weighted index is ecause there is no change in the market value. (For stock split calculation refer ppendix 4.0.)

.3.3) Monetary Aggregates M1 (Narrow Money)

It is a monetary aggregates total M1 including currency in circulation plus lemand deposits. Measures of the money supply, commonly defined as notes and coins n circulation plus bank deposits that are available on demand. These figures show nonetary growth rates as percentage changes over the corresponding period in the revious year. Data is taken from central bank monthly statistical bulletin.

.3.4) Interest Rates

The interest rates in saving deposits for commercial banks are used. Movement in nterest rates significantly affects volume of shares traded, cost of corporate borrowing nd the outlook of the economy.

I Test Models

For the purpose of analyses, the first analysis (Analysis Model 1) that is the ationship analysis will adopt the regression analysis using the ordinary least squares LS) method with applying the log linear functional form. Then using the same method d the same functional form, we then used the dummy variable to ascertain the effect on alaysian Stock Index Futures before and after the July 1997 financial crisis.

The second part (Analysis Model 2) saw two alternative forecasting methods have en used to forecast Stock Index Futures data namely Moving Averages (MA) and ngle Exponential Smoothing for forecasting technique ability to test market efficiency. ıese time-series forecasting treats the system as a black box and makes no attempt to scover the factors affecting its behavior. Therefore, it is much more different as the recast of the future is based on past values of a variable and / or past errors, but not the planatory variables which may effect the system. The objective of such time series recasting methods is to discover the pattern in the historical data series and extrapolate at pattern into the future. Then using trading rules and assumptions we'll begin to lculate the profit and loss for all the trades. With fully technical way of trading; just ving order to buy when we forecast market up and sell order when we forecast market ıwn; it will be tremendous to find out that using the forecast method and trading rules hether market could be outperformed or could not be outperformed.

The third part (Analysis Model 3) is the regression forecasting analysis using mple forecasting; where the log linear functional form with lagged period (t-1) in all e independent variables for 60 observations is applied. To forecast the second bservation of the Stock Index Futures figure, the first observation data for all dependent variables are used. The same method and form then are also used for the gression on the dummy variables. After getting the forecasted data for all three models, en using the same trading rules and assumptions in Analysis Model 2, we'll begin to lculate the profit and loss and test for market efficiency.

The fourth part (Analysis Model 4) is the forecasting technique ability to utperform the market using the ex-post sample data for its forecasting period. Here, stead of 60 observations, the sample is divided into two halves. The first half consists f the monthly data observation 1 to 30, i.e. January 1996 to June 1998 (30 observations). he second half consists of the monthly data from observations 31 –60 i.e. July 1998 to ecember 2000 (30 observations). In the ex-post forecast, observation 1 to 30 is used in e regression; the result is then used to forecast observation 31. The same procedure is peated. Observation 1 to 31 is used in the regression, and the result is then used to recast observation 32. This is done until all the observations in the second half of the mple has been forecasted. Lastly the same procedure on trading rules and assumptions ave been applied to investigate for market efficiency.

.5 Analysis Model 1- The Econometric Model and Econometric Dummy Model for Relationship Analysis

Econometric Model was adopted in regression for the first section of the egression analysis. In order to ascertain whether the sign of the four selected indicators bove is the same before and after crisis[1], Econometric Dummy Model was applied on he data.

.5.1 Multiple Variable Regression Model

The general form of multiple regressions is:

$$Y_t = b_t0 + b1\ X_t1 + b2\ X_t2 + \ldots\ldots\ldots\ldots + bk\ X_t k + u_t \qquad (4.5.1)$$

Where Y_t is the dependent variable; X_t1, $X_t2 \ldots X_tk$ is the explanatory variables , explanatory variable 2......... explanatory variable k (or regressors), u is the listurbance term, b_t0 is the intercept and all b1,b2.....bk are the coefficients. Thus in ur case, if stock index futures were the dependent variable, factors namely futures olume, market capitalization, M1 and interest rates could be tested for their influence on tock index futures by using the multiple variable regression model.

5.2 Regression on Dummy Variable

The creation of the new variable to allow time-related feature of the data will be used our Econometric Dummy Model. The determination of time separation is before and :er July 1997. It is because the classification of data before July 1997 shows data longs before the time of financial crisis in Asia. July 1997 was chosen because that is ɜ month when speculators' attack on Thai Baht occurred on 2nd July 1997. The below proach is used to apply dummy variable for this research:

D0 = 0 if any part of the data period falls before July 1997

D1 = 1 if any part of the data period falls after July 1997

For the regression on dummy variables, consider the following model:

$$= \mathbf{b0 + b1X1 + b2X2 + \ldots\ldots\ldots\ldots + bnXn + bn{+}1\ DUM + e} \qquad \textbf{(4.5.2)}$$

Note that (4.5.2) is like the multiple regression model encountered previously but ›w adding up with a dummy variable DUM (hereafter, we shall designate all dummy ıriables by the letter DUM). Model (4.5.2) may enable us to find out whether there are ıall or enormous changes on the dependent variables, which is Stock Index Futures :fore and after July 1997 crisis.

'uly 1997 was chosen as the turning point to separate the period before and after crisis as the selling of ıth thus created the domino effect of currencies selling in East Asian started on 2nd July 1997.

5.3 Functional Form of Regression Model

The log linear model was used in both regression analysis; multiple regression ıd dummy variable regression.

$$\text{ı } Yi = \alpha + \beta 1 \ln X_i + \ + \beta 2 \ln X_j \ldots\ldots + u_i \qquad (4.5.3)$$

The linear model was transformed to the log-linear model for regression to ırmulate 'new smaller data' compared to the original data for the purpose of trouble-free ı regression and interpretation. One more attractive feature of using log-linear model is ıat the slope coefficient β1 measures the elasticity of Y with respect to X, that is, the ɜrcentage change in Y for a given (small) percentage change in X. This is so important ı our study as we would like to discover what is the percentage change in stock index ıtures for a given change in the independent variables.

Therefore, for the purpose of the study, the multiple variable regression model sing the log linear functional form for the original model is:

ı FUTS t = f (ln VOL t , ln MARCAP t, ln M1 t, ln SAVDEP t,)

ı FUTS t = b1 + b2lnVOL + b3 lnMARCAP + b4lnM1 + b5lnSAVDEP

'otes on variables:

ı FUTS	=	log Stock Index Futures
ı VOL	=	log Stock Index Futures' volume
ı MARCAP	=	log Market Capitalization of the Kuala Lumpur Stock Exchange
ı M1	=	log Monetary Aggregates represented by M1
ı SAVDEP	=	log Interest Rates in term of saving deposits for commercial banks.
1	=	intercept
2, b3 ,b4 ,b5	=	the coefficients

Whereas the multiple variable regression model on dummy variable using the log .near functional form is:

n FUTS t = (ln VOL t , ln MARCAP t, ln M1 t, ln SAVDEP t, ln DUM97)

n FUTS t = b1 + b2lnVOL + b3lnMARCAP + b4lnM1 + b5lnSAVDEP +)6lnDUM97

Dummy July 1997

0 if before July 1997

1 if after July 1997

Votes on variables:

n FUTS	=	log Stock Index Futures
n VOL	=	log Stock Index Futures' volume
n MARCAP	=	log Market Capitalization of the Kuala Lumpur Stock Exchange
n M1	=	log Monetary Aggregates represented by M1
n SAVDEP	=	log Interest Rates in term of saving deposits for commercial banks.
)UM97=		Dummy variable.
)1	=	intercept
)2, b3 ,b4 ,b5	=	the coefficients

Analysis Model 2- Moving Averages and Single Exponential Smoothing – recasting Technique Ability With Trading Rules and Assumptions to Test ırket Efficiency.

The simple methods to test the market efficiency are using time series forecasting hniques namely the simple moving averages and single exponential smoothing. In this ılysis, the 'past history' of Stock Index Futures data could be smoothed in many ways. section 4.6.1, we will consider the simple averaging methods, namely the simple ving averages. The forecast is denoted by Ft.

.1 Moving Averages

One way to modify the influence of past data on the mean-as-a forecast is to ecify at the outset just how many past observations will be included in a mean. The m "moving averages" is used to describe this procedure because as each new servation becomes available, a new average can be computed by dropping the oldest servation and including the newest one. This moving average will then be the forecast the next period. The number of data points in each average remains constant and ludes the most recent observations.

A moving average forecast of order k, or MA (k), is given by:

$$_{+1} = 1 / k \sum_{i=t-k+1}^{t} Y_i \qquad (4.6.1.1)$$

In this moving averages method, the objective here is that we are forecasting the ext observation by taking an average of the most recent observations. We use MA (k) to enote a moving average forecast of order k and k MA to denote a moving average moother of order k. Algebraically, the simple average model uses a simple average of ıe k most recent values of the time series variable:

$$F_{t+1} = \frac{Y_t + Y_{t-1} + Y_{t-2} + \ldots\ldots\ldots Y_{t-k+1}}{k} \quad (4.6.1.2)$$

However for MA (1), that is, a moving average of order 1 – the last known data oint (Yt) is taken as the forecast for the next period ($F_{t+1} = Y_t$). An example of this is " ıe forecast of tomorrow's closing price of IBM stock is today's closing price." This was alled the naïve forecast.

For example, if we take k as 3 or MA (3), the forecast for April data is taken to be ıe average of January, February and March data:

ΛA (3) : April's forecast = (March data + February data + January data) / 3

ΛA (3) : May's forecast = (April data + March data + February data) / 3

For the purpose of this study, the writer has chosen MA (2), MA (3), MA (4), MA 5) and MA (6) to forecast the Stock Index Futures data and to test the market efficiency. ıfter having the forecast data, using the trading rules and assumptions (refer section .8.3), we then try to test whether we could make above average returns on overall trades.

;.2 *Single Exponential Smoothing*

Suppose we wish to forecast the next value of our time series Y_t which is yet to observed. The forecast is denoted by Ft. When the observation Y_t becomes available, : forecast error is found to be $Y_t - F_t$. The method of single exponential forecasting takes : forecast for the previous period and adjusts it using the forecast error. That is, the ecast for the next period is:

$$_{t+1} = F_t + \alpha\,(Y_t - F_t) \qquad \textbf{(4.6.2.1)}$$

iere α is a constant between 0 and 1.

It can be seen that the new forecast is simply the old forecast plus *an adjustment* · *the error* that occurred in the last forecast. When α has a value close to 1, the new ecast will include a substantial adjustments for the error in the previous forecast. nversely, when α is close to 0, the new forecast will include very little adjustment. us, the effect of a large or small α is completely analogous (in an opposite direction) to : effect of including a small or a large number of observations when computing a ving average. The equation (4.6.2.1) involves a basic principle of negative feedback, ice it works much like the control process. The past forecast error is used to correct the xt forecast in a direction opposite that of the error. There will be adjustment until the or is corrected. Another way of writing (4.6.2.1) is:

$$_{+1} = \alpha Y_t + (1 - \alpha)\,F_t \qquad \textbf{(4.6.2.2)}$$

The forecast (F_{t+1}) is based on weighting the most recent observation (Y_t) with a ght value (α) and weighting the most recent forecast (F_t) with a weight of 1- α. ιation (4.6.2.2) is the general form used in exponential smoothing methods. One can :cast with single exponential smoothing by using either equation (4.6.2.1) or (4.6.2.2). example to forecast the observation no 12 then:

$$2 = \alpha Y11 + (1-\alpha) F11 \tag{4.6.2.3}$$

Therefore in order for us to forecast, we need to determine the value of α for ιstments. For the purpose of this study, the writer has determined to choose various ιes of α close to 1 such as 0.8,0.9,0.99,0.999 and 0.9999, which will include more ιstment and also choose the α values close to 0 such as 0.0001, 0.001, 0.01, 0.1, and which will include very little adjustment to the forecasting model. Last but not least writer has also chosen α = 0.5 the middle value between 0 to 1. The writer has sen various values of α in order to test both side values between 0 and 1.

Figure 4.3

α Values Chosen

	Extreme Cases			Close to 0		Middle Point		Close to 1	Extreme Cases		
ied	0.0001	0.001	0.01	0.1	0.2	0.5	0.8	0.9	0.99	0.999	0.9999

After having the forecast data, using the same trading rules and assumptions (refer ion 4.8.3), we then try to test for efficiency.

4.7 Analysis Model 3- The Log Linear Distributive Lag Model and Log Linear Distributive Lag Dummy Model for Sample Forecasting Technique Ability With Trading Rules and Assumptions to Test Market Efficiency.

4.7.1 The Log-Linear Distributive Lag Model.

One of the major objectives of econometrics is forecasting. In this section, we will apply the in sample forecast. The sample data used in the regression analysis are 60 observations. The lag factor of t-1 indicates that using the first observation (observation no 1.) for the independent variables to forecast the next observations (observation no 2.) for the dependent variables. We will use the January 1996 data for all independent variables namely Stock Index Futures' volume, market capitalization, M1 and interest rate to forecast Stock Index Futures February 1996 data. In order to forecast using log-linear distributive lag method, the general function and equation used are as below:

$$\mathbf{lnFUTS = f\,(lnVol_{t-1}, lnMarCap_{t-1}, lnM1_{t-1}, lnSavDep_{t-1})}$$

$$\mathbf{lnFUTS = b1 + b2\ lnVol_{t-1} + b3\ lnMarCap_{t-1} + b4\ lnM1_{t-1} + b5\ lnSavDep_{t-1}}$$

Notes on variables:

ln FUTS	=	log Stock Index Futures
ln VOL	=	log Stock Index Futures' volume (lag one period)
ln MARCAP	=	log Market Capitalization of the Kuala Lumpur Stock Exchange (lag one period)
ln M1	=	log Monetary Aggregates represented by M1 (lag one period)
ln SAVDEP	=	log Interest Rates in term of saving deposits for commercial banks. (lag one period)
b1	=	intercept
b2, b3 ,b4 ,b5	=	the coefficients

After we regress the data using above equation, we'll derive the sign for all the independent variables and coefficients for each bs in the above equations. Then keyed in all the data for all observations, calculate the point forecast figures for next observations on Stock Index Futures. Then apply trading rules and assumptions (refer 4.8.3).

4.7.2 The Log Linear Distributive Lag Dummy Model.

For the log linear lag dummy model, the methodology applied almost the same but now we used the dummy variable in the model.

The approach to apply dummy variable for this research:

D0: if any part of the data period falls before July 1997

D1: if any part of the data period falls after July 1997

$$\mathbf{lnFUTS = f\,(\,lnVol_{t-1},\ ln\ MarCap_{t-1},\ LnM1_{t-1},\ lnSavDep_{t-1},\ lnDUM97_{t-1})}$$

$$\mathbf{lnFUTS = b1 + b2\ lnVol_{t-1} + b3\ lnMarCap_{t-1} + b4\ lnM1_{t-1} + b5\ lnSavDep_{t-1} + b6\ lnDUM97_{t-1}}$$

Notes on variables:

ln FUTS	=	log Stock Index Futures (current period)
ln VOL t-1	=	log Stock Index Futures' volume (lag one period)
ln MARCAP	=	log Market Capitalization of the Kuala Lumpur Stock Exchange (lag one period)
ln M1	=	log Monetary Aggregates represented by M1 (lag one period)
ln SAVDEP	=	log Interest Rates in term of saving deposits for commercial banks. (lag one period)
LnD97	=	log Dummy variable (lag one period)
b1	=	intercept
b2, b3 ,b4 ,b5,b6	=	the coefficients

It is the same approached as the previous log linear distributive lag model. After we regress the data using above equation, we'll derive the sign for all the independent variables and coefficients for each bs in the above equations. Then keyed in all the data for the rest of the observations, calculate the point forecast figures for next observations on Stock Index Futures. Then apply trading rules and assumptions (refer 4.8.3) to investigate winning and losses trades.

4.8 Analysis Model 4- The Log Linear Distributive Lag Model and Log Linear Distributive Lag Dummy Model for Ex-Post Forecasting Technique Ability With Trading Rules and Assumptions to Test Market Efficiency.

4.8.1 The Log Linear Distributive Lag Model for Ex-Post Forecasting Technique Ability With Trading Rules and Assumptions to Test Market Efficiency

For this analysis, we split the data into 2 that the last 30 observations remain our ex-post data. Using the log linear distributive lag model, we regress the first 30 observations (1-30) to get the regression equation:

Regression 1-30:

$$\ln FUTS_{30} = f(\ln VOL_{29}, \ln MARCAP_{29}, \ln M1_{29}, \ln SAVDEP_{29})$$

$$LnFUTS_{30} = b1 + b2 \ln VOL_{29} + b3 \ln MARCAP_{29} + b4 \ln M1_{29} + b5 \ln SAVDEP_{29}$$

Notes on variables:

ln FUTS	=	log Stock Index Futures
ln VOL	=	log Stock Index Futures' volume
ln MARCAP	=	log Market Capitalization of the Kuala Lumpur Stock Exchange
ln M1	=	log Monetary Aggregates represented by M1
ln SAVDEP	=	log Interest Rates in term of saving deposits for commercial banks.
b1	=	intercept
b2, b3 ,b4 ,b5	=	the coefficients

After getting the intercept and the coefficients for all the independent variables then for forecast the ex-post data (data no 31), using the same regression equation, we fill in the data observations no 31 for all independent variables.

Forecast data number 31

$\ln FUTS_{31}$ = b1 + b2 lnVOL **(data lag no 30 in observation 31)** **+ b3 lnMARCAP** **(data lag no 30 in observation 31)** **+ b4 lnM1** **(data lag no 30 in observation 31)** **+ b5 lnSAVDEP** **(data lag no 30 in observation 31)**

Notes on variables:

ln FUTS = log Stock Index Futures for observation and no 31
ln VOL = log Stock Index Futures' volume(data lag no 30 in observation 31)
ln MARCAP = log Market Capitalization of the Kuala Lumpur Stock Exchange(data lag no 30 in observation 31)
ln M1 = log Monetary Aggregates represented by M1(data lag no 30 in observation 31)
ln SAVDEP = log Interest Rates in term of saving deposits for commercial banks. (data lag no 30 in observation 31)
b1 = intercept
b2, b3 ,b4 ,b5 = the coefficients

The data is only possible to regress on the last trading day of the month where the Stock Index Futures value for observation no 30 is only available to be captured at that particular period only; that is the closing price on the last trading day of the month. Then take the data lag no 30 for all independent variables (in observation 31), plugged in to the equation to get the Stock Index Futures value for observation 31.

For the next observation (1-31), another regression needs to be conducted.

Regression 1-31:

$$\ln FUTS_{31} = f(\ln VOL_{30}, \ln MARCAP_{30}, \ln M1_{30}, \ln SAVDEP_{30},)$$

$$\ln FUTS_{31} = b1 + b2 \ln VOL_{30} + b3 \ln MARCAP_{30} + b4 \ln M1_{30} + b5 \ln SAVDEP_{30}$$

Notes on variables:

ln FUTS	=	log Stock Index Futures
ln VOL	=	log Stock Index Futures' volume
ln MARCAP	=	log Market Capitalization of the Kuala Lumpur Stock Exchange
ln M1	=	log Monetary Aggregates represented by M1
ln SAVDEP	=	log Interest Rates in term of saving deposits for commercial banks.
b1	=	intercept
b2, b3 ,b4 ,b5	=	the coefficients

After getting the intercept and the coefficients for all the independent variables then for forecast the ex-post data (data no 32), using the same regression equation, we fill in the data observations no 32 for all independent variables.

Forecast data number 32

$$\ln FUTS_{32} = b1 + b2 \ln VOL_{\text{(data lag no 31 in observation 32)}} + b3 \ln MARCAP_{\text{(data lag no 31 in observation 32)}} + b4 \ln M1_{\text{(data lag no 31 in observation 32)}} + b5 \ln SAVDEP_{\text{(data lag no 31 in observation 32)}}$$

Notes on variables:

ln FUTS = log Stock Index Futures for observation and no 32

ln VOL = log Stock Index Futures' volume(data lag no 31 in observation 32)

ln MARCAP = log Market Capitalization of the Kuala Lumpur Stock Exchange(data lag no 31 in observation 32)

ln M1 = log Monetary Aggregates represented by M1(data lag no 31 in observation 32)

ln SAVDEP = log Interest Rates in term of saving deposits for commercial banks. (data lag no 31 in observation 32)

b1 = intercept

b2, b3 ,b4 ,b5 = the coefficients

The same methodology is repeated for the rest of the ex-post data, which each ew data need to be regressed and forecasted. Then use the same trading rules and ssumptions (refer section 4.8.3) test for the weak form efficiency.

.8.2 The Log Linear Distributive Lag Dummy Model for Ex-Post Forecasting Technique ıbility With Trading Rules and Assumptions to Test Market Efficiency

For the model using dummy variable, we again split the sample data into 2 that he last 30 observations remain our ex-post data. Using the log linear distributive lag nodel, we regress the first 30 observations (1-30) to get the regression equation:

Regression 1-30:

$$\ln FUTS_{30} = f(\ln VOL_{29}, \ln MARCAP_{29}, \ln M1_{29}, \ln SAVDEP_{29}, \ln DUM_{29})$$

$$\ln FUTS_{30} = b1 + b2 \ln VOL_{29} + b3 \ln MARCAP_{29} + b4 \ln M1_{29} + b5 \ln SAVDEP_{29} + b6 \ln DUM_{29}$$

Notes on variables:

ln FUTS	=	log Stock Index Futures
ln VOL	=	log Stock Index Futures' volume
ln MARCAP	=	log Market Capitalization of the Kuala Lumpur Stock Exchange
ln M1	=	log Monetary Aggregates represented by M1
ln SAVDEP	=	log Interest Rates in term of saving deposits for commercial banks.
ln DUM	=	log dummy.
b1	=	intercept
b2, b3 ,b4 ,b5	=	the coefficients

After getting the intercept and the coefficients for all the independent variables then for forecast the ex-post data (data no 31), using the same regression equation, we fill in the data observations no 31 for all independent variables.

Forecast data number 31

lnFUTS $_{31}$ = b1 + b2 lnVOL(data lag no 30 in observation 31) + b3 lnMARCAP (data lag no 30 in observation 31) + b4 lnM1(data lag no 30 in observation 31) + b5 lnSAVDEP(data lag no 30 in observation 31) + b6 lnDUM(data lag no 30 in observation 31)

Notes on variables:

ln FUTS = log Stock Index Futures for observation and no 31
ln VOL = log Stock Index Futures' volume(data lag no 30 in observation 31)
ln MARCAP = log Market Capitalization of the Kuala Lumpur Stock Exchange(data lag no 30 in observation 31)
ln M1 = log Monetary Aggregates represented by M1(data lag no 30 in observation 31)
ln SAVDEP = log Interest Rates in term of saving deposits for commercial banks. (data lag no 30 in observation 31)
ln DUM = log dummy (data lag no 30 in observation 31)
b1 = intercept
b2, b3 ,b4 ,b5 = the coefficients

The data is only possible to regress on the last trading day of the month where the Stock Index Futures value for observation no 30 is only available to be captured at that particular period only; that is the closing price on the last trading day of the month. Then take the data lag no 30 for all independent variables (in observation 31), plugged in to the equation to get the Stock Index Futures value for observation 31.

For the next observation (1-31), another regression needs to be conducted.

Regression 1-31:

$$\mathbf{lnFUTS_{31} = f\,(lnVOL_{30}\,,\,lnMARCAP_{30},\,lnM1_{30},\,lnSAVDEP_{30},\,lnDUM_{30})}$$

$$\mathbf{lnFUTS_{31} = b1 + b2lnVOL_{30} + b3\ lnMARCAP_{30} + b4\ lnM1_{30} + b5\ lnSAVDEP_{30} + b4\ lnDUM_{30}}$$

Notes on variables:

ln FUTS	=	log Stock Index Futures
ln VOL	=	log Stock Index Futures' volume
ln MARCAP	=	log Market Capitalization of the Kuala Lumpur Stock Exchange
ln M1	=	log Monetary Aggregates represented by M1
ln SAVDEP	=	log Interest Rates in term of saving deposits for commercial banks.
ln DUM	=	log dummy.
b1	=	intercept
b2, b3 ,b4 ,b5	=	the coefficients

After getting the intercept and the coefficients for all the independent variables then for forecast the ex-post data (data no 32), using the same regression equation, we fill in the data observations no 32 for all independent variables.

Forecast data number 32

$$\mathbf{lnFUTS_{32} = b1 + b2\ lnVOL_{(data\ lag\ no\ 31\ in\ observation\ 32)} + b3\ lnMARCAP_{(data\ lag\ no\ 31\ in\ observation\ 32)} + b4\ lnM1_{(data\ lag\ no\ 31\ in\ observation\ 32)} + b5\ lnSAVDEP_{(data\ lag\ no\ 31\ in\ observation\ 32)} + b6\ lnDUM_{(data\ lag\ no\ 31\ in\ observation\ 32)}}$$

Notes on variables:

ln FUTS = log Stock Index Futures for observation and no 32
ln VOL = log Stock Index Futures' volume(data lag no 31 in observation 32)
ln MARCAP = log Market Capitalization of the Kuala Lumpur Stock Exchange(data lag no 31 in observation 32)
ln M1 = log Monetary Aggregates represented by M1(data lag no 31 in observation 32)
ln SAVDEP = log Interest Rates in term of saving deposits for commercial banks. (data lag no 31 in observation 32)
ln DUM = log dummy. (data lag no 31 in observation 32)

b1	=	intercept
b2, b3 ,b4 ,b5	=	the coefficients

The same methodology and procedures are repeated for the rest of the ex-post data, which each new data need to be regressed and forecasted. Then use the same trading rules and assumptions (refer section 4.8.3), test the market efficiency by investigate whether the market could be outperformed or not.

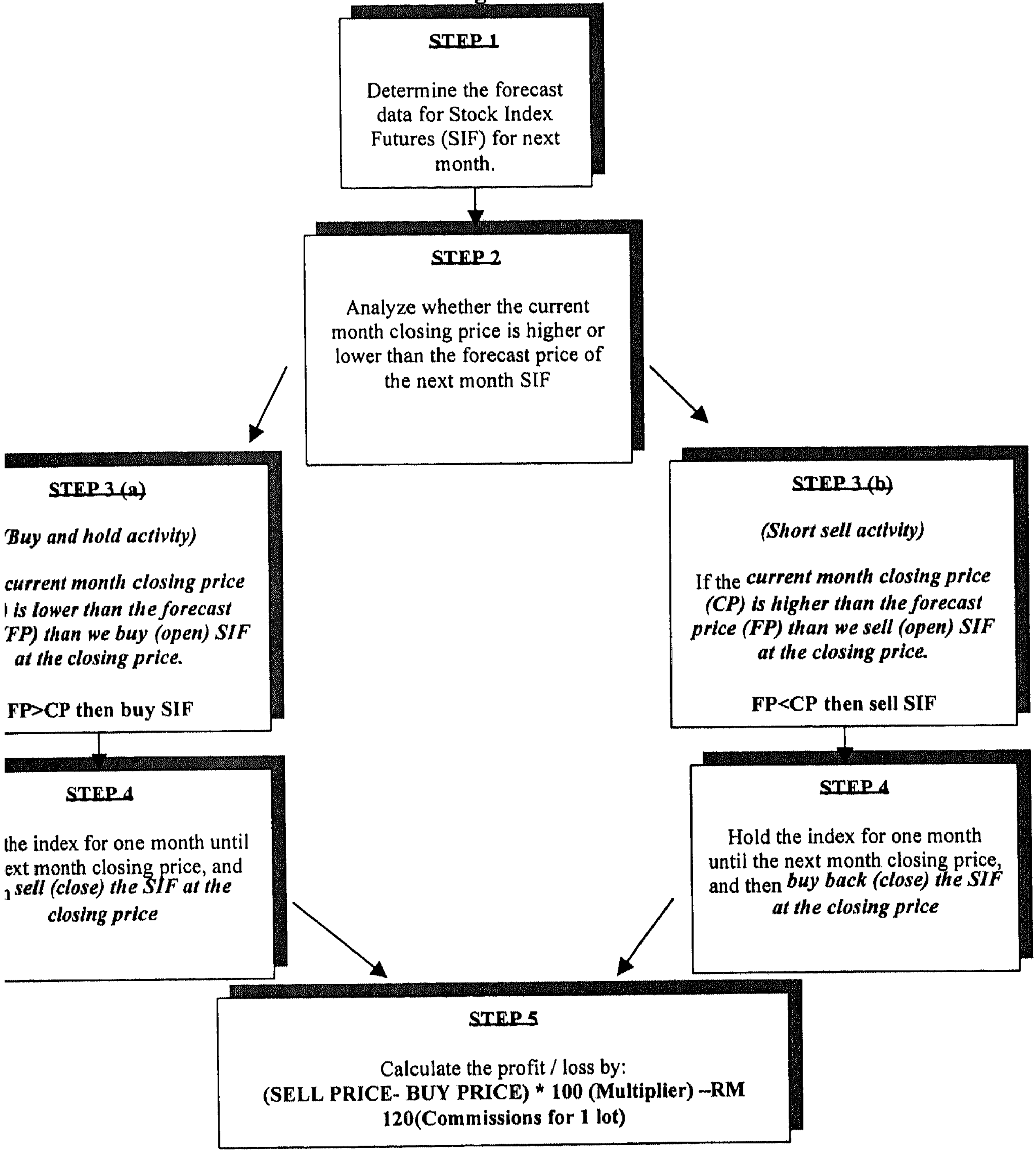
4.8.3 The Trading Rules and Assumptions

After we forecast next observation period using the moving averages, single exponential smoothing, econometric model and econometric dummy model [use the current economic indicators data (this month Stock Index Futures' volume data, Market Capitalization data, M1 data and interest rates data)], we could derive the Stock Index Futures (SIF) forecasting data of the next month. Using the SIF forecast data, what we have to do is to look at the magnitude; up or down of the forecast data compared to the current closing prices. If the forecast index shows up for the next month closing price, then regardless what price the forecast index shows, we have to buy first at the current closing price of the SIF and sell later at the next month closing price because we will follow the tenet of the trading rules which say " Buy Low, Sell High".

Vice versa, if the forecasting index shows down for next month regardless what price the forecast index shows, we have to sell first at the closing price and buy back later at the next month closing price. Then, the differences between buy and sell activities will be calculated for each periods to know the profit and loss for each period and we will examine whether using this fully technical analysis and demolish the emotion factors in it, we can outperform the market; meaning whether we could gain above-average returns from the market. If this mechanism shows that the market can be outperformed, then the Malaysian Stock Index Futures market can be considered as in the weak form inefficiency market. If this mechanism did not offer any advantages, the market could be safely concluded as weak form efficient.

Figure 4.3

The Trading Mechanism



Assumptions:

1. The index we buy and sell are the closing price of the month.
2. The trade will ignore the slippage (the cost of not getting the exact price in the real trade)
3. For simplicity, we will assume that the closing price of the month will be exactly the same of the opening price of the next month.
4. The cost for 1 lot is RM120 or 1.2 points per round turn.