Chapter 2

Principles, Model specification and Literature review

2.1 Principles, Models, Rationale or Hypothesis

In this study, the relationship between Gold Spot price and Gold Future price in Thailand Future Exchange (TFEX) will be studied under principles as followed:

2.1.1 Future on Commodities

Gold is the commodity under consideration. There is a relationship between Gold Spot price and Gold Future price as:

$$F = Se^{r(T-t)} \tag{2.1}$$

where

F	=	Future Price of gold
S	=	Spot price of gold
e	=	An irrational constant approximately equal to 2.718281828
r	=	Risk free rate
$T-t$	=	contract term (years)

2.1.2 Cost of Carry model

Cost of Carry approach shows the relationship between Gold Future price and Gold Spot price. But there are differences among futures contracts. Then the Cost of Carry formulas depend to what type of futures contracts under consideration as:

- For non-dividend paying back stock, the cost of carry is r, since there are no storage costs and no income is earned.

$$F = Se^{r(T-t)} \tag{2.2}$$

- For stock an index, the cost of carry is $r-q$, since q is rate of income earned.

$$F = Se^{(r-q)(T-t)} \tag{2.3}$$

- For a currency, the cost of carry is $r-r_f$, since r_f is a foreign rate.

$$F = Se^{(r-r_f)(T-t)} \tag{2.4}$$

- For a commodity with a proportion of storage cost(u), the cost of carry is $r+u$.

$$F = Se^{(r+u)(T-t)} \tag{2.5}$$

2.1.3 Rate of Return

Rate of return or return of investment, in financial term can be calculated as:

$$ROR = ln\left(\frac{p_t}{p_{t-1}}\right) \tag{2.6}$$

where

p_t = Final value after investment

p_{t-1} = Initial value of investment

2.1.4 Time Series

Time series are data or observations which have been changing along times. There might be either stationary or non-stationary changing for time series. If time series is able to explain or analyze the changes in the past, then those time series can be used as a tool to predict or estimate the future.

The time series used should be stationary. There are ways to test whether time series are stationary or non-stationary. One of them is the Box-Jenkins Method of Time-Series Analysis (Autocorrelation Coefficient Function: ACF). Another is Dickey–Fuller's called unit root as would be study further.

Stationary Stochastic Process: "A stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed." (Gujarati, 2004 pg.797)

Let X_t be a stochastic time series with these properties:

Mean: $E(x_t) \;=\; \mu$

Variance: $var(x_t) \;=\; E(x_t-\mu)^2 = \sigma^2$

Covariance: $\gamma_k \;=\; E[(x_t-\mu)(x_{t+k}-\mu)] \;=\; \sigma_k - \mu$

1. Unit Root Test

Unit root test is a test of stationary using autoregressive model. In this study, the ADF (augmented Dickey-Fuller test) is used, start at:

$$x_t \;=\; \rho x_{t-1} + e_t \qquad (2.7)$$

where

x_t, x_{t-1} = Variable time series at time t and $t-1$

ρ = Autocorrelation coefficience

e_t = Random error

If $\rho = 1$, that is unit root and that also means that they are non-stationary stochastic process. That brings the hypotheses as:

H_0 : $\rho = 1$

H_a : $|\rho| < 1$: $-1 < \rho < 1$

If H_0 is accepted, that means they are unit root and non-stationary.

Equation 2.2 can be manipulated by subtracting X_{t-1} on both sides as:

$$x_t - x_{t-1} = \rho x_{t-1} - x_{t-1} + e_t$$

$$= (\rho - 1)x_{t-1} + e_t$$

$$\Delta x_t = \delta x_{t-1} + e_t \qquad (2.8)$$

Where $\delta = \rho - 1$, which also means that if $\delta = 0$ then $\rho = 1$ and that H_0 is accepted. In another way round, if $\delta = 1$ then $\rho = 0$ and that H_a is accepted and they are stationary. Then the hypotheses can be written as:

H_0 : $\delta = 0$

H_a : $\delta < 1$

If $\delta = 0$ or $\rho = 1$, from equation 2.3 we get,

$$\Delta x_t = e_t \qquad (2.9)$$

Augmented Dickey–Fuller (ADF) test is used in this study. It is a version for larger and more complicated set of time series models. It was assumed that the error term e_t are correlated. It is negative number, the more negative is the stronger the rejection of the null hypothesis ($H_0 \ : \ \rho = 1$) that it is unit root at a level of confidence. Then those three DF tests are:

1. Test for a unit root:

$$\Delta x_t \quad = \quad \delta x_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta x_{t-i} + e_t \qquad (2.10)$$

2. Test for a unit root with drift:

$$\Delta x_t \quad = \quad \beta_1 + \delta x_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta x_{t-i} + e_t \qquad (2.11)$$

3. Test for a unit root with drift and deterministic time trend:

$$\Delta x_t \quad = \quad \beta_1 + \beta_2 t + \delta x_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta x_{t-i} + e_t \qquad (2.12)$$

where

β_1, β_2, δ = Parameters

t = Trend

Terms added are $\sum_{i=1}^{m} \alpha_i \Delta x_{t-i}$, they are lagged difference terms. Those help in making DW (Durbin–Watson statistic) to get closer to 2.

To test the hypothesis in all three cases, we estimate the test equation by least squares and examine the t-statistic for the hypothesis that $\delta = 0$. Those t-statistic values must be compared to specially generate critical values. The Dickey-Fuller critical values are more negative than the standard critical values. This simplify that the calculated t-statistic must be larger than usual for the null hypothesis of non-stationary $\delta = 0$.

2. Lag Length Criteria

Vector autoregressive (VAR) models are widely used in forecasting and in analysis of the effects of structural shocks. A critical element in the specification of VAR models is the determination of the lag length of the VAR. There are many criteria used to determine lag length, criteria which have been used to evaluate in this study are:

1. Sequential modified LR test statistic

$$LR \quad = \quad (T-m)\{log|\Omega_{l-1}| - log|\Omega|\} \sim \chi^2(k^2)$$

2. Final prediction error

$$FPE_P = \ln(\hat{\sigma}^2)\,(n+p)(n-p)^{-1}$$

3. Akaike information criterion

$$AIC_P \; = \; n\ln(\hat{\sigma}^2) + 2p$$

4. Schwarz information criterion

$$SIC_P \; = \; n\ln(\hat{\sigma}^2) + n^{-1}p\ln(n)$$

5. Hannan-Quinn information criterion

$$HQC_P = \; n\ln(\hat{\sigma}^2) + 2n^{-1}p\ln(\ln(n))$$

Between Akaike information criterion (AIC) and Schwarz information criterion (SIC). There is unexplained variation in the dependent variable and the number of explanatory variables increase the value of Schwarz information criterion (SIC). Lower SIC implies either fewer explanatory variables, better fit, or both. The SIC generally penalizes free parameters more strongly than does the Akaike information criterion (AIC).

3. Cointegration Test

As a general rule, non-stationary time series variables should not be used in regression models, to avoid the problem of spurious regression. If y_t and x_t are nonstationary $I(1)$ variables, then their difference or any linear combination of them is expected, such that, $e_t = y_t - \beta_1 - \beta_2 x_t$ to be $I(1)$ as well. However, there is an important case when $e_t = y_t - \beta_1 - \beta_2 x_t$ is a stationary $I(0)$ process. In this case y_t and x_t are coinegrated. Cointegration implies that y_t and x_t share similar stochastic trends and since ε_t is stationary they would not be much different.

In this study Johansen Cointegration Test, a multivariate version of the univariate DF test. Consider a reduced form VAR of order p:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + +Bx_t + \varepsilon_t$$

where y_t is a k-vector of I(1) variables, x_t is a n-vector of deterministic trends, and ε_t is a vector of shocks. We can rewrite this VAR as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i y_{t-i} + Bx_t + \varepsilon_t$$

where

$$\Pi = \sum_{i=1}^{p} A_i - 1, \Gamma_i = -\sum_{j=i+1}^{p} A_j$$

The Π matrix represents the adjustment to disequilibrium following an exogenous shock. If Π has reduced rank $r < k$ where r and k denote the rank of Π and the number of variables constituting the long-run relationship, respectively, then there exist two $k \times r$ matrices α and β, each with rank r, such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is stationary. r is called the cointegration rank and each column of β is a cointegrating vector (representing a long-run relationship). The elements of the α matrix represent the adjustment or loading coefficients, and indicate the speeds of adjustment of the endogenous variables in response to disequilibrating shocks, while the elements of the Γ matrices capture the short-run dynamic adjustments. Johansen's method estimates the Π matrix from an unrestricted VAR and tests whether we can reject the restrictions implied by the reduced rank of Π. This procedure relies on relationships between the rank of a matrix and its characteristic roots (or eigenvalues). The rank of Π equals the number of its characteristic roots that differ from zero, which in turn corresponds to the number of cointegrating vectors.

4. Vector Autoregression (VAR) models

In cointegration relationship we assumed that y_t is dependent variable and x_t is independent variable and treat the relationship between these two as regression model. But we can still do it another way round as y_t for independent variable and x_t as dependent variable. Then we have two possible regression models relating them are:

$$y_t = \beta_{10} + \beta_{11}x_t + e_t^y \quad , \quad e_t^y \sim N\left(0, \sigma_y^2\right) \tag{2.13}$$

$$x_t = \beta_{20} + \beta_{21}y_t + e_t^x \quad , \quad e_t^x \sim N(0, \sigma_x^2) \tag{2.14}$$

In this two series system there can be only one relationship between x_t and y_t and so it must be the case that $\beta_{21} = \frac{1}{\beta_{11}}$ and $\beta_{20} = -\frac{\beta_{10}}{\beta_{11}}$. And x and y are normalized by this two equations and then we can start discussing the vector autoregressive (VAR) models by:

$$y_t = \beta_{10} + \beta_{11}y_{t-1} + \beta_{12}x_{t-1} + v_t^y \tag{2.15}$$

$$x_t = \beta_{20} + \beta_{21}y_{t-1} + \beta_{22}x_{t-1} + v_t^x \tag{2.16}$$

These two equations describe a system in which each variable is a function of its own lag, and the lag of the other variable in the system. Equation 2.17, y is a function of its own lag y_{t-1} and the lag of other variable x_{t-1}. Equation 2.18, x is a function of its own lag x_{t-1} and the lag of other variabley_{t-1}. Together the eqation constitute a system known as a vector autoregressive (VAR) and since the maximum lag is of order 1, we have a VAR(1).

If x and y are stationary $I(0)$ variables, the above system can be estimated using least squares applied to each equation. If x and y are non-stationary $I(1)$ and not cointegrated, we work with the first differences. In this case, the VAR model is

$$\Delta y_t = \beta_{11}\Delta y_{t-1} + \beta_{12}\Delta x_{t-1} + v_t^{\Delta y} \tag{2.17}$$

$$\Delta x_t = \beta_{21}\Delta y_{t-1} + \beta_{22}\Delta x_{t-1} + v_t^{\Delta x} \tag{2.18}$$

All variables are stationary $I(0)$, and the system can again be estimated by least squares. The VAR model is a general framework to describe the dynamic interrelationship between stationary variables. If x and y are stationary $I(0)$ variables, the system will be used. But if they are not cointegrated, the interrelation between them using a VAR framework differences. If they are non-stationary $I(1)$ and cointegrated, we need to modify the system of equation to allow for the cointegrated relationship between the $I(1)$ variables.

5. Impulse responses

Impulse response functions are techniques which used to analyze problems in macroeconomics and also are functions show the effects of shocks on the adjustment path of the variables.

- **The Univariate Case**

Consider a univariate series $y_t = \rho y_{t-1} + v_t$ and subject it to a shock of size v in period 1. Assume an arbitrary starting value of y at time zero: $y_0 = 0$. At time $t = 1$, following the shock, the value of y will be: $y_1 = \rho y_0 + v_1 =$

v. Assume that there are no subsequent shocks in later time periods ($v_2 = v_3 = \cdots = 0$), at time $t = 2$, $y_2 = \rho y_1 = \rho v$, at time $t = 3$, $y_3 = \rho y_2 = \rho(\rho y_1) = \rho^2 v$ and so on. Thus the time path of y following the shock is$\{v, \rho v, \rho^2 v, \cdots\}$. The value of the coefficients $\{1, \rho, \rho^2, \cdots\}$ are known as multipliers, and the time path of y following the shock is known as the impulse response function.

- **The Bivariate Case**

Consider an impulse response function analysis with two time series based on a bivariate VAR system of stationary variables:

$$y_t = \delta_{10} + \delta_{11} y_{t-1} + \delta_{12} x_{t-1} + v_t^y \tag{2.19}$$

$$x_t = \delta_{20} + \delta_{21} y_{t-1} + \delta_{22} x_{t-1} + v_t^x \tag{2.20}$$

In this case, there are two possible shocks to the system, one to y and another to x, then, there would be four impulse response functions as:

- The effect of a shock to y on the time path of y and x.
- The effect of a shock to x on the time path of y and x.

The actual mechanics of generating impulse responses in a system is complicated by;

1. One has to allow for interdependent dynamics (the multivariate analog of generating the multipliers)
2. One has to identify the correct shock from unobservable data.

From these two complications lead to what is known as the identification problem. If there is no identification problem, the system would be as described in equation 2.26 and 2.27. There is a true representation of the dynamic system, y is related only to lags of y and x, and x is related only to lags of y and x. In another words, is related only to lags of y and x are related in a dynamic but not contemporaneously. The current value is related only to lags of x_t does not appear in the equation for y_t and the current value y_t does not appear in the equation for x_t. Also, we need to assume the errors v_t^x and v_t^y are independent of each other and $v^y \sim N(0, \sigma_y^2)$ and $v^x \sim N(0, \sigma_x^2)$.

Consider the case when there is a one standard deviation shock to y so that at time $t = 1, v_t^y = \sigma_y = 0$. Assume $v_t^x = 0$ for all t. It is traditional to consider a standard deviation shock rather than a unit shock to overcome measurement issue. Assume $y_0 = x_0 = 0$. Since we are focusing on how a shock changes the paths of y and x, we can ignore the intercepts, then;

1. When $t = 1$, the effect of a shock of size σ_y on y is

   $y_1 = v_1^y = \sigma_y,$

   and the effect on x is

   $x_1 = v_1^x = 0.$

2. When $t = 2$, the effect of the shock on y is

   $y_2 = \delta_{11} y_1 + \delta_{12} x_1 = \delta_{11} \sigma_y + \delta_{12} 0 = \delta_{11} \sigma_y$

   and the effect on x is

   $x_2 = \delta_{21} y_1 + \delta_{22} x_1 = \delta_{21} \sigma_y + \delta_{22} 0 = \delta_{21} \sigma_y$

3. When $t = 3$, the effect of the shock on y is

   $y_3 = \delta_{11} y_2 + \delta_{12} x_2 = \delta_{11} \delta_{11} \sigma_y + \delta_{12} 0 = \delta_{11} \delta_{11} \sigma_y$

   and the effect on x is

   $x_3 = \delta_{21} y_2 + \delta_{22} x_2 = \delta_{21} \delta_{21} \sigma_y + \delta_{22} 0 = \delta_{21} \delta_{21} \sigma_y$

By repeating the substitutions for $t = 4,5,\cdots$ we obtain the impulse response of the shock to y on y as $\sigma_y\{1, \delta_{11}, (\delta_{11}\delta_{11} + \delta_{12}\delta_{21}), \cdots\}$ and the impulse response of the shock to y on x as $\sigma_y\{0, \delta_{21}, (\delta_{21}\delta_{11} + \delta_{22}\delta_{21}), \cdots\}$

If there is one standard deviation shock to x so that at time $t = 1, v_1^x = \sigma_x$. Two periods after the shock, the effect of a shock of size σ_x on y is $y_1 = v_1^y = 0$, and the effect of the shock on x is $x_1 = v_1^x = \sigma_x$. Two periods after the shock, when $t = 2$, the effect on y is

$$y_2 = \delta_{11}y_1 + \delta_{12}x_1 = \delta_{11}0 + \delta_{12}\sigma_x = \delta_{12}\sigma_x$$

and the effect on x is

$$x_2 = \delta_{21}y_1 + \delta_{22}x_1 = \delta_{21}0 + \delta_{22}\sigma_x = \delta_{22}\sigma_x$$

By repeating the substitutions for $t = 4,5,\cdots$ we obtain the impulse response of the shock to x on y as $\sigma_x\{0, \delta_{12}, (\delta_{21}\delta_{12} + \delta_{12}\delta_{22}), \cdots\}$ and the impulse response of the shock to x on x as $\sigma_x\{1, \delta_{22}, (\delta_{21}\delta_{12} + \delta_{22}\delta_{22}), \cdots\}$

The advantage of examining impulse response functions (and not just VAR coefficients) is that they show the size of the impact of the shock plus the rate at which the shock dissipates, allowing for interdependencies.

6. Least Squares Estimation

Another way to estimate the relationship and make use of the sample observation is Least Squares Estimation. There is the way to estimate the line of data we have and the intercept and slope of this line can tell us the relationship between them. The line which best fit the data using the least squares principle are b_1 and b_2, the least squares estimates of β_1 and β_2 (the parameter of relationship in the regression analysis). Then comes the least squares equation that is:

$$\hat{y}_i = b_1 + b_2 x_i \tag{2.21}$$

The vertical distances from each point to the fitted line are the least squares residuals. They are given by

$$\hat{e}_i = y_i - \hat{y}_i = y_i - b_1 + b_2 x_i \tag{2.22}$$

The least squares estimators:

$$b_2 = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})^2} \tag{2.23}$$

$$b_1 = \bar{y} - b_2 \bar{x} \tag{2.24}$$

Where $\bar{y} = \frac{\sum y_i}{N}$ and $\bar{x} = \frac{\sum x_i}{N}$ are the sample means of the observations on y and x.

- **Coefficient of determination (R^2)**

From equation 2.22 we can derive that:

$$y_i - \hat{y}_i = \hat{e}_i \tag{2.25}$$

$$y_i - \bar{y} = (\hat{y}_i - \bar{y}) + \hat{e}_i \tag{2.26}$$

$$\sum(y_i - \bar{y})^2 = \sum(\hat{y}_i - \bar{y})^2 + \sum \hat{e}_i^{\ 2} \tag{2.27}$$

where

$\sum(y_i - \bar{y})^2$	=	Total sum of squares: SST (total variation in y)
$\sum(\hat{y}_i - \bar{y})^2$	=	Sum of squares due to the regression: SSR (explained sum of squares)
$\sum \hat{e}_i$	=	Sum of squares due to error: SSE (unexplained sum of squares)

From these abbreviations then comes;

$$SST = SSR + SSE \tag{2.28}$$

The decomposition of the total variation in y in to a part that is explained by the regression model and a part that is unexplained allows us to define a measure, coefficient of determination (R^2). That is the proportion of variation in y esplained by x within the regression model.

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{2.29}$$

The closer to 1, the closer the sample values y_i are to the fitted regression equation $\hat{y}_i = b_1 + b_2 x_i$. If $R^2 = 1$, then all the sample data fall exactly on the fitted least squares line, so $SSE = 0$ and the model fits the data perfectly. If they are uncorrelated and show no linear association, then the least squares fitted line is identical to $\bar{y}$, so that $SSR = 0$ and $R^2 = 0$. When $0 < R^2 < 1$, means that the proportion of the variation in y about its mean that is explained by the regression model.

- **Durbin-Watson (DW) Statistic**

Durbin–Watson statistic is a test statistic used to detect the presence of autocorrelation (a relationship between values separated from each other by a given time lag) in the residuals (prediction errors) from a regression analysis. The hypotheses usually considered in the Durbin-Watson test are:

$$H_0 \;:\; \rho = 0$$

$$H_a \;:\; \rho = 1$$

with the test statistic:

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=2}^{n} {e_i}^2}$$

Where i is the number of observations, $d = 2$ indicates no autocorrelation. The value of d always lies between 0 and 4. If the Durbin–Watson statistic is substantially less than 2, there is evidence of positive serial correlation. If Durbin–Watson is less than 1.0, there may be values of d indicate successive error terms are, on average, close in value to one another, or positively correlated. If $d > 2$ successive error terms are, on average, much different in value to one another.

7. Cointegrating Regression

If these variables under the study are cointegrated. We only focus on the classical analysis of $I\,(1)$ and $I\,(0)$ systems and estimate the Vector Autoregressive (VAR) model as the equations 2.19 and 2.20.

$$\Delta y_t = \beta_{11}\Delta y_{t-1} + \beta_{12}\Delta x_{t-1} + v_t^{\Delta y}$$

$$\Delta x_t = \beta_{21}\Delta y_{t-1} + \beta_{22}\Delta x_{t-1} + v_t^{\Delta x}$$

As we can see that lag length in these equations are t and $t-1$. But in time series data of limited length, this assumption of errors is violated if a relationship between and is insignificant; that is if lag length is 0. Vector Autoregression (VAR) model would not fit the estimation anymore. We should estimate the cointegration regression to study the relationship in this case.

Engle and Granger (1987) note that a linear combination of two or more $I\,(1)$ series may be stationary, or $I\,(0)$, in which case we say the series are cointegrated. Such a linear combination defines a cointegrating equation with cointegrating vector of weights characterizing the long-run relationship between the variables. Consider the $n+1$ dimensional time series process, with cointegrating equation:

$$y_t = x_t'\beta + D_{1t}'\gamma_1 + u_{1t}$$

where

$D_t \quad = \quad (D_{1t}' D_{1t}')' \quad = \quad$ Deterministic trend repressor

and the regressors equations are:

$$x_t = \Gamma_{21}' D_{1t} + \Gamma_{22}' D_{2t} + \varepsilon_{2t}$$

$$\Delta\varepsilon_{2t} = u_{2t}$$

- **Dynamic OLS**

Jose G. Montalvo (1994)'s study compared the estimator efficiency among OLS (Ordinary Least Squares) estimator, CCR (Canonical Cointegration Regression) estimator, CCRPW (CCR estimator using a VAR pre-whitened kernel estimator of the long-run covariance matrix) and DOLS (Dynamic OLS) estimator. The result of this study shows that DOLS estimator has smaller bias and root mean squared error than the other estimators.

Chen, McCoskey, and Kao (1996) investigated the finite sample proprieties of the OLS estimator, the t-statistic, the bias-corrected OLS estimator, and the bias-corrected t-statistic. They found that the bias-corrected OLS estimator does not improve over the OLS estimator in general. The result of their study suggests that alternatives, such as the FMOLS (Fully Modified OLS) estimator or the DOLS (Dynamic OLS) estimator may be more promising in cointegrated regression.

2.2 Literature Review

Chris Brooks, Alistair G. Rew and Stuart Ritson examined the lead–lag relationship between the FTSE 100 index and index futures price employing a number of time series models. Using 10-min observations from June 1996–1997, it is found that lagged changes in the futures price can help to predict changes in the spot price. The best forecasting model is of the error correction type, allowing for the theoretical difference between spot and futures prices according to the cost of carry relationship. This predictive ability is in turn utilized to derive a trading strategy which is tested under real-world conditions to search for systematic profitable trading opportunities. It is revealed that although the model forecasts produce significantly higher returns than a passive benchmark, the model was unable to outperform the benchmark after allowing for transaction costs.

Engle, Robert F. & Granger, C. W. J. studied the relationship between co-integration and error correction models, first suggested in Granger (1981), is here extended and used to develop estimation procedures, tests, and empirical examples. If each element of a vector of time series X_t first achieves stationary after differencing, but a linear combination $\alpha X_t'$, is already stationary, the time series xt are said to be co-integrated with co-integrating vector α. There may be several such co-integrating vectors so that α becomes a matrix. Interpreting $\alpha' X_t, = 0$ as a long run equilibrium, co-integration implies that deviations from equilibrium are stationary, with finite variance, even though the series themselves are non-stationary and have infinite variance. The paper presents a representation theorem based on Granger (1983), which connects the moving average, autoregressive, and error correction representations for co-integrated systems. A vector auto-regression in differenced variables is incompatible with these representations. Estimation of these models is discussed and a simple but asymptotically efficient two-step estimator is proposed. Testing for co-integration combines the problems of unit root tests and tests with parameters unidentified under the null. Seven statistics are formulated and analyzed. The critical values of these statistics are calculated based on a Monte Carlo simulation. Using these critical values, the power properties of the tests are examined and one test procedure is recommended for application. In a series of examples it is found that consumption and income are co-integrated, wages and prices are not, short and long interest rates are, and nominal GNP is co-integrated with M2, but not M1, M3, or aggregate liquid assets.

Heany, Richard studied Data on commodity prices from the London Metals Exchange was used to examine the connection between factors of the cost-of-carry relationship, spot price, futures price, interest rate to maturity, and stock level effects. Results for the commodity of lead support unit root processes for interest rates and stock levels. However, results for spot price and futures price are unconfirmed.

Lucy F. Ackert and Marie D. Racine used a no-arbitrage, cost-of-carry pricing model to examine whether equity spot and futures markets are cointegrated. A stock index and its futures price should be cointegrated if the cost of carry is stationary. Otherwise, the appropriate co-integrating relationship is trivariate and includes the index, futures price, and cost of carry. This paper studies the relationships among the Standard and Poor's 500 index, associated index futures price series, and interest rate for January 4, 1988, through June 30, 1995, and finds that all three series are non-stationary. This paper further finds that the index and futures price are not cointegrated unless the cost of carry is included in the co-integrating relationship. These findings are consistent with the no-arbitrage pricing model and do not appear to be sensitive to the presence of structural breaks in the series.

Montalvo, Jose G. compared the finite sample performance of the canonical correlation regression estimator (CCR) and Stock and Watson's (A simple estimator of cointegration vectors in higher order integrated systems, Econometrica, 1993, 61(4), 783-820) dynamic ordinary least squares estimator (DOLS) using the models proposed by Inder. The CCR estimator shows smaller bias than the OLS and the fully modified. The DOLS estimator performs systematically better than the CCR estimator.

Nimanussornkul, Chaiwat investigated volatility and volatility spillovers of returns across the financial markets and across the countries in South-East Asia. The daily returns of each market are used to model the volatility and asymmetric effects. Univariate conditional volatility and multivariate conditional volatility are employed. The univariate conditional volatility models report that the coefficients in the conditional variance equations are most significant in both the short and long run. This means that the volatility in each market is changing over time. Moreover, asymmetric effects in stock markets are found in the Indonesia and Singapore stock markets, but without leverage. In contrast, Indonesia and Philippines bond markets show leverage. Therefore, investors should be aware of time-varying risk in SouthEast Asia financial markets, as well as the different impacts of positive and negative shocks in Indonesia and Singapore stock markets, and the Indonesia and Philippines bond markets.

The CCC model reports that the estimated correlations of stock markets yield the constant conditional correlation in most cases. Moreover, a portfolio that is constructed from assets in Vietnam and Malaysia stock markets can diversify portfolio risk efficiently. Investors can diversify risk by investing in the Thai bond market and other countries' stock markets. For bond markets, the results of CCC suggest that including only Singapore and Thai bonds in portfolios can achieve lower risk. The results of VARMA-GARCH for each pair of assets between stock and bond markets show that the Thai stock market and the other bond markets have volatility spillovers to each other. For pairs of assets in stock markets, the volatility spillovers between the markets are mixed. Based on the data since the year 2000, asymmetric effects for each pair of assets in nearly every country were found. For the bond market, the results suggest that they have no volatility spillovers for the Thai bond market based on VARMA-GARCH and VARMA-AGARCH models. The study only in bond markets, the results show that the Singapore bond market volatility has spillovers to other bond markets, such that the volatility of a developed country affects the volatility of developing countries. Speculators may operate in developing countries, particularly Indonesia and Philippines, to earn capital gains from volatile markets.

The DCC reports that, for both stock and bond, coefficients estimated are significantly different from zero, which means that the conditional correlations are time-varying, so that constant condition correlations do not hold.

Supornjag, Jutamas analyzed fluctuation of rate of return of stock index futures in the derivative market using ARIMA-EGARCH model. The study investigated the stock index futures in four countries: Thailand, the United States of America, Japan, and Hong Kong by using time-series data of closing price reported since April, 28th 2007 to May, 31st 2008. The result of the unit root test revealed that the rate of return of stock index futures in the four countries was stable. Finally, this study concludes that the appropriate model for forecasting the rate of return of stock index in each market is different depending on the movement of stock price in each country. That would help investors understand the fluctuation patterns of the rate of return of stock index futures, and then they can manage their investments according to their investment goal further.

Taka, Angkana analyzed the relationship between fold price and oil price in Thailand using co-integration method. Three prices are selected in this study, namely bullion price, ornaments price and Dubai oil price. The results show that both gold prices and oil prices have a unit root and the same order of integration. To the co-integration method, the empirical results indicate that the estimated residuals are stationary. Thus, gold prices and oil price have the relationship in long term and two-way relationship in short-term.

Paspipatkul, Patairat investigated the domestic price transmission analysis employed Vector Autoregressive Model (VAR) and Vector Error Correction Model (VEC). The result shows the appropriate lags orders equals 2 and the long-term equilibrium exists with Cointegration Vector (r) equals to 2. The RSS1 of Haad Yai was determined by its own price lagged by 1 period (coefficient - -0.0808). However, no factors were found to be significantly related to RSS3 of Haad Yai. Market efficiency study was analyzed by Cointegration and Error Correction Model. Since it was not apparent if risk premium exist in rubber futures trading, two scenarios, i.e. with and without risk premium were assumed.

Results of the analyses for with and without risk premium models reject the null hypothesis of unbiasedness fir the Kuala Lumper, London and New York exchanges as related to Haad Yai RSS1 but do not reject null hypothesis for the Singapore futures exchange. As for RSS3 of Haad Yai, the hypothesis was also rejected for the same futures exchanges in addition to the Tokyo and Kobe markets. The results of market efficiency analysis for the Songkla port reveal that the hypothesis cannot be rejected for the Kuala Lumper, London and Singapore RSS1 and RSS3 for with and without risk premium models (but be rejected for New York RSS1) As for the Bangkok port, the hypothesis testing shows that Kuala Lumper and Singapore futures prices were also unbiased predictors of the Bangkok RSS3 F.O.B. prices. It can be asserted that there exists oversea futures prices appropriate for predicting the future spot prices of rubber sheets in Thailand and the Singapore exchange was found to be unbiased price predictor for both grades of rubber in all three spot markets in Thailand.