Chapter 3

The Effects of Oil Prices on Asia Stock Indexes

At present, Asia with the strongest rise in demand over the last year has come to the top of its production capacities. The oil depletion certainly will influence the economic development of the emerging Asian countries. ‘‘Oil is so significant in the international economy that forecasts of economic growth are routinely qualified with the caveat: ‘provided there is no oil shock.’’ (Robert W. Faff, 1999)

This Thesis shows model of univariate volatility and bivariate volatility in VARMA-GARCH model (Ling, S., and M. McAleer, 2003). The Singapore oil price in log return is presented that It has time-varying correlations in dynamic conditional correlation with the others log return of Asia stock index. The time-varying correlations in dynamic conditional correlation multivariate model DCC, the regime-switching SETAR (Self Exciting Threshold Autoregressive model) and smooth transition conditional correlation model, LSTAR (Logistic Smooth Threshold Autoregressive model) are presented in the thesis.

This chapter is a revised version from the original paper presented at the Second Conference of The Thailand Econometric Society, Chiang Mai, Thailand in Appendix.

Abstract

This paper provides evidence regarding the role of oil prices on the weekly Thai and Asia stock indexes, namely Nikkei 225 (Nikkei Stock Average 225), Tokyo Stock Exchange, ALL (ASX All Ordinaries index), Australian Securities Exchange, KLSE (KLSE Composite Index), Malaysian stock market, TWSE (Taiwan's composite Index), Taiwan Stock Exchange, BSESN (Bombay SE Sensitive Index), Bombay Stock Exchange, movements using time-varying conditional correlations. Oil price changes are found to play an important role in all stock markets, except BSESN. Compared with a bivariate model without any explanatory variables, the inclusion of oil price changes increases the persistence of time-varying correlations in a dynamic conditional correlation model. Furthermore, a regime-switching smooth transition conditional correlation model shows that conditional correlations increase during periods of volatility.

Keywords: Dynamic conditional correlations, Smooth transition, Oil prices.

JEL classification codes:

C22, C32, G17, G32, Q43.

3.1 Introduction

At present, the world energy needs come from exhaustible resource about 85 percent, uranium and mainly fossil fuels. The oil supply covers with about 34 % by far the largest share followed by coal (24%), natural gas (21.5%), nuclear (5.5%) and renewables (15%), including traditional biomass.

One third of these sources is used for electricity production of about 16,000 Terawatt hours. Electricity is produced from coal (~39%), gas (~18%), renewables (~18%), and nuclear energy (~17%), followed by a small amount from oil (7.5%). Within the renewables about 90% of the electricity come from hydropower, 5% from biomass and a small amount (<1%) from wind and other sources (China and India Insight, 2007). Industrialized countries consume about 5-6 kW on average. This includes countries like USA or Canada with more than 10 kW. Most important will be the development of China (at present ~1.3 kW) and India (~0.5 kW) with a total of 2.3 billion people (Zitel).

Asia with the strongest rise in demand over the last year has come to the top of its production capacities. The oil depletion certainly will influence the economic development of the emerging Asian countries China and India. The Asian oil balance is highly negative since Asia is a huge net importer of oil. China became the world's second largest oil consumer with close to 6 Mb/day behind the USA (~20 Mb/day) and in front of Japan with 5.4 Mb/day. While Japan has to import all of its oil, China produced about 55% from domestic sources. But while the demand strongly increases, domestic production is flat and within this decade will presumably start to decline. India's production covers only about 30 percent of consumption with a declining share. At present, it consumes the same amount of oil as South Korea needs. The latter, however, has to import all of its demand from international oil markets. Malaysia is Asia's only remaining oil exporting country, since Indonesia's production decline over the last years forced the country to switch to a net importer in March 2004. Given the fact, that the emerging markets in China and India show strong growth rates, Asia as a region shows by far the strongest growth in energy (and especially oil) demand for the last decade. Therefore Asia will be strong hit by the beginning supply scarcity of oil.

''Oil is so significant in the international economy that forecasts of economic growth are routinely qualified with the caveat: 'provided there is no oil shock.'' (Robert W. Faff, 1999) Sadorsky confirms that oil prices and oil price volatility both play important roles in affecting economic activity (Sadorsky, 1999). His results suggest that changes in oil prices impact economic activity but, changes in economic activity have little impact on oil prices. Impulse response functions show that oil price movements are important in explaining movements in stock returns. The positive shocks to oil prices depress real stock returns while shocks to real stock returns have positive impacts on interest rates and industrial production. There is also evidence that oil price volatility shocks have asymmetric effects on the economy. There are the dynamic interactions among interest rates, real oil prices, real stock returns, industrial production and the employment. The oil prices are also important in explaining stock price movements. For both specifications the results suggest that a positive oil price shock depresses real stock returns. Stock returns do not rationally signal (or lead) changes in real activity and employment (Papapetrou, 2001).

China and India became the world's largest oil consumer. Oil price movement is often indicative of inflationary pressure in the economy and depresses real stock returns. The impact of oil price changes may have on Asia stock index. Weekly data are used. The study investigates the nature of co-movements between oil prices on the weekly Thai and Asia stock index movements using time-varying conditional correlations. Compared with a bivariate model without any explanatory variables, the inclusion of oil price changes increases the persistence of time-varying correlations in a dynamic conditional correlation multivariate model. The regime-switching smooth transition conditional correlation model investigates the nature of potential time variation in the correlations of shocks to these two variables; oil prices and Asia stock index.

The hypotheses of the research are set up as (1) the oil prices effect to the Asia stock indexes; especially Thai stock index (2) the regime-switching smooth transition conditional correlation model captures the volatility better than dynamic conditional correlation multivariate model because the correlations have increased between the oil price and the Asia stock index over time.

3.2 Model Specifications

Time-Varying Correlation Models

The mean and volatility equations, with the following two subsections describing the Dynamic conditional and smooth transition correlation models are discussed in this section.

The Dynamic conditional and smooth transition models then differ in their definitions of ρ_t. The constant conditional correlation (CCC) model simply assumes that ρ_t is constant over time (McMaleer, 2005,Bauwens, L., S. Laurent and V.K. Rombouts, 2006).

Dynamic Conditional Correlation Model

Engle (2002) specifies the dynamic conditional correlation model through the GARCH(1,1)-type process

$$q_{i,j,t} = \bar{\rho}_{12}(1-\alpha-\beta) + \alpha\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \beta q_{i,j,t-1} \quad (1)$$

Where $\bar{\rho}_{12}$ is the (assumed constant) unconditional correlation between $\varepsilon_{1,t}$ and $\varepsilon_{2,t}, \alpha$, is the news coefficient and β is the decay coefficient. In order to constrain the conditional correlation ρ_t to lie between -1 and +1, $q_{1,2,t}$ from (1) and the conditional correlation is obtained from

$$\rho_t = q_t /(q_{11}, q_{22,t})^{1/2} \quad (2)$$

The model is mean-reverting provided $\alpha + \beta < 1$, and when the sum is equal to 1 the conditional correlation process in (1) is integrated (Ling, S., and M. McAleer, 2003 a , Nektarios Aslanidis, 2007).

Smooth Transition Conditional Correlation Models

The smooth transition conditional correlation model considered by Silvennoinen and Terasvirta (2005) assumes the conditional correlation ρ_t follows

$$\rho_t = \rho_1(1 - G_t(S_t;\gamma,c)) + \rho_2 G_t(s_t;\gamma,c) \quad (3)$$

in which the transition function $G_t(s_t;\gamma,c)$ is assumed continuous and bounded by zero and unity, γ and c are parameters, whereas s_t is the transition variable. A plausible and widely used specification for the transition function is the logistic function

$$(G_t(s_t;\gamma,c) = 1/1 + \exp[-\gamma(s_t - c)], \gamma > 0 \quad (4)$$

where the parameter c is the threshold between the two regimes. The slope parameter γ> 0 determines the smoothness of the change in the value of the logistic function and thus the speed of the transition from one correlation state to the other. When $\gamma \to \infty, G_t(s_t;\gamma,c)$ becomes a step function $(G_t(s_t;\gamma,c)=0$ if s_t < c their transition variable can be deterministic or stochastic. $(G_t(s_t;\gamma,c)=1 \cdot if \cdot s_t > c)$, and the transition between the two extreme correlation states becomes abrupt. The (smooth) change between correlation regimes, and as $\gamma \to \infty$ captures a structural break in the correlations (Bwo-Nung Huang, 2005 and Annastiina Silvennoinen, 2007). The Pooled AIC are used for selecting Smooth Transition Conditional Correlation Models (philip Hans Franses, 2004). The alternative AIC for 2-regime SETAR model as the sum of AICs for AR models in the two regimes, that is

$$AIC(p_1,p_2) = n_1 \ln \hat{\sigma}_1^2 + n_2 \ln \hat{\sigma}_2^2 \\ + 2(p_1+1) + 2(p_2+1)$$

where n_j ,j=1,2, is the number of observations in the j_{th} regime,and $\hat{\sigma}_{\grave{e}}^2$, j=1,2,,is the variance of the residuals in the j_{th} regime. The BIC for a SETAR model can be defined analogously as

$$BIC(p_1,p_2) = n_1 \ln \hat{\sigma}_1^2 + n_2 \ln \hat{\sigma}_2^2 \\ + (p_1+1)\ln n_1 + (p_2+1)\ln n_2$$

For given upper bounds p_1^* and p_2^*, respectively, the selected lag orders in the two regimes are those for which the information criterion is minimized.

The SETAR model assumes that the threshold variable q_t is chosen to be a lagged value of the time series itself. The model is assumed in both regimes, a 2-regime SETAR model is given by

$$\rho_t = \begin{cases} \varphi_{0,1} + \varphi_{1,1}\rho_{t-1} + \varepsilon_t & \text{If } \rho_{t-1} \le c. \\ \varphi_{0,2} + \varphi_{1,2}\rho_{t-1} + \varepsilon_t & \text{If } \rho_{t-1} > c. \end{cases}$$

An alternative way to write the SETAR model is

$$\rho_t = \left(\varphi_{0,1} + \varphi_{1,1}\rho_{t-1}\right)\left(1 - I\left[\rho_{t-1} > c\right]\right) + \left(\varphi_{0,2} + \varphi_{1,2}\rho_{t-1}\right) I\left[\rho_{t-1} > c\right] + \varepsilon_t$$

where I [A] is an indicator function with I [A]=1 if the event A occurs and I [A] = 0 otherwise.

The SETAR model assume that the border between the two regime is given by a specific value of the threshold variable In particular, in the 2-regime SETAR model, y_D will be estimated within the y_{t-1} (Philip Hans Franses, 2004 and Zivot., 2006).

Testing for constant correlations in a multivariate GARCH model

Lagrange Multiplier (LM) (Tse.Y.K., 2000) detects the constant-correlation hypothesis in a multivariate GARCH model. The constant-correlation model set the conditional variances of y_{it} follow a GARCH process, while the correlations are constant. Denoting $\Gamma=\{\rho_{ij}\}$ as the correlation matrix, we have

$$\sigma_{it}^2 = \omega_i + \alpha_i \sigma_{i,t-1}^2 + \beta_i y_{i,t-1}^2, i = 1,\ldots,K \qquad (5)$$

$$\sigma_{ijt} = \rho_{ij}\sigma_{it}\sigma_{jt}, 1 \le i < j \le K \qquad (6)$$

The assumption ω_i, α_i and β_i are nonnegative, $\alpha_i + \beta_i < 1$, for i=1,2,K and Γ is positive definite. The LM test can then be applied to test for the restrictions. This approach only requires estimates under the constant-correlation model, and can thus conveniently exploit the computational simplicity of the model.

There are $N=K^2+2K$ parameters in the extended model with time-varying correlations. The constant-correlation hypothesis can be tested by examining the hypothesis $H_0: \delta_{ij} = 0,\ 1 \le i < j \le K$ Under H_0, there are M=K(K-1)/2 independent restrictions. The optimal properties under the null H_0 is the LM test .The model which is deified standardised residual as $\varepsilon_{it} = y_{it} / \sigma_{it}$ might be written as

$$\rho_{ijt} = \rho_{ij} + \delta'_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1} \tag{7}$$

As ε_{it} depends on other parameters of the model through σ_{it}, analytic derivation of the LM statistic is intractable. The LM statistic of H_0 under the above framework which denote D_t as the diagonal matrix with diagonal elements given by σ_{it} , and $\Gamma=\{\rho_{ijt}\}$ as the time-varying correlation matrix.

The LM statistic for H_0 can be calculated using the following formula

$$LMC = \hat{s}'\left(\hat{S}'\hat{S}\right)^{-1}\hat{s} \tag{8}$$

$$= l'\hat{S}\left(\hat{S}'\hat{S}\right)^{-1}\hat{S}'l, \tag{9}$$

where l is the T*1 column vector of ones and $\hat{S}$ is S evaluated $\hat{\theta}$. Under the usual regularity conditions LMC is asymptotically distributed as $\chi 2_M$. Eq. (9) shows that LMC can be interpreted as T times R^2, where R^2 is the uncentered coefficient of determination of the regression of l on $\hat{S}$. It is well-known that other forms of the LM statistic are available. For example, further simplification can be obtained by making use of the fact that in $\hat{S}'\,l$ the elements corresponding to the unrestricted parameters is zero. Eq. (9) is a convenient form.

$$d_{it} = 1 + \sum_{h}^{P} \alpha_{ih} d_{i,t-h}$$

$$e_{iht} = \sigma_{i,t-h}^{2} + \sum_{h'=1}^{P} \alpha_{ih'} e_{ih,t-h'},$$

$$f_{ikt} = \sum_{h=1}^{P} \alpha_{ih} f_{ik,t-h} + y_{i,t-k}^{2}$$

$$\sigma_{it}^{2} = \omega_{i} + \sum_{k=1}^{P} \alpha_{ih} \sigma_{i,t-1}^{2} + \sum_{k=1}^{q} \beta_{ik} y_{i,t-k}^{2}, i = 1,\dots,K$$

The first partial derivatives of l_t with respect to ω_i, α_{ih} and β_{ik} (p+q+1 derivatives altogether) can be calculated with e_{iht} and f_{ikt} replacing e_{it} and f_{it}, respectively.

3.3 Data and Estimation

3.3.1 Data

The raw weekly data, Nikkei 225 (Nikkei Stock Average 225), Tokyo Stock Exchange, ALL (ASX All Ordinaries index), Australian Securities Exchange, KLSE (KLSE Composite index), Malaysian stock market, TWSE (Taiwan's composite index), Taiwan Stock Exchange, are collected from Reuters for the period 10 January 1982 to 6 June 2008. The BSESN (Bombay SE Sensitive index) Bombay Stock Exchange is collected from Reuters for the period 7 January 1990 to 6 June 2008.

Oil price

Crude oil, also known as petroleum, is the world's most actively traded commodity. The largest markets are in London, New York and Singapore but crude oil and refined products - such as gasoline (petrol) and heating oil - are bought and sold all over the world. The oil price information appearing in Asia almost reference from Singapore International Monetary Exchange, (SIMEX). The rationale for employing weekly synchronous data in modeling stock returns. The oil prices data are available on weekly basis from website (see http://tonto.eia.doe.gov/dnav/pet/pet_pri_spt_s1_w.htm)

3.4 Empirical Results

The descriptive statistics for rates of return of the all indexes and oil price rates of return are presented in Table 1. The Nikkei 225 (Nikkei Stock Average 225) has the lowest mean rates of return at -0.05, while The TWSE (Taiwan's composite index) and the BSESN (Bombay SE Sensitive index) have the highest mean rates of return at 0.14 ,0.3 respectively. The others have similar means rates of return at 0.1. The maxima of all standard deviation series differ substantially, with The TWSE (Taiwan's composite index) displaying the highest maxima while The ALL (ASX All Ordinaries index) displays the lowest. Each of the series displays a high degree of kurtosis. Although the Skewness varies slightly, ranging from -4.36 for ALL (ASX All Ordinaries index) to -0.01 for BSESN (Bombay SE Sensitive index).Table 2 provides the ADF, Phillips-Perron (PP) and K.P.S.S unit root tests for the all indexes, as well as their log differences (or rates of return). The original time series in logarithms are checked for stationary. It is clear that the indexes are non-stationary, while their rates of return are stationary. The results of rates of return are stationary are compared with the 1 % critical values to indicate rejection of the unit root null hypothesis. The results of K.P.S.S unit root tests are compared with the 1 % critical values to indicate non-rejection of the stationary null hypothesis.

Table 1: Descriptive Statistics for Asian Stock Index Returns

Statistic	Singapore Gasoline	All Ordinaries Index	KLSE Composite Index	Nikkei 225	Taiwan's Composite Index	Bombay SE Sensitive Index
Mean	0.19	0.10	0.10	-0.05	0.14	0.31
Median	0.18	0.23	0.25	0.10	0.36	0.40
Maximum	25.25	7.09	24.58	11.05	24.76	23.00
Minimum	-18.78	-34.81	-29.40	-12.79	-24.61	-18.30
Std. Dev.	3.70	2.14	3.33	2.84	4.73	3.95
Skewness	0.07	-4.36	-0.65	-0.21	-0.12	-0.01
Kurtosis	7.99	69.23	14.11	4.59	6.49	5.46
Jarque-Bera	1140.20	203980.94	5720.96	123.63	555.34	242.05
Prob	0.00	0.00	0.00	0.00	0.00	0.00
Obs	1097.00	1097.00	1097.00	1097.00	1086.00	956.00

Testing for constant correlations in a multivariate GARCH model

The LM test can be interpreted as times R^2, where R^2 is the uncentered coefficient of determination of the regression. It is well-known that other forms of the LM statistic are available. The Testing for constant correlations in a multivariate GARCH model results are summarized in Table 3.

Table 2: Unit Root Tests for Weekly Stock Indexes and Oil Price indexes

unit root test	ADF-test		PP -test	KPSS-test	ADF-test		PP	KPSS
	t-Statistic	Lag Length	Adj. t-Stat	LM-Stat.	t-Statistic	Lag Length	Adj. t-Stat	LM Stat.
Singapore gasoline	4.575	1	4.707	2.355	-15.452	2	-25.252	0.260
All Ordinaries index	0.414	0	0.265	3.585	-8.893	13	-27.538	0.090
KLSE Composite index	-1.36	0	-1.661	1.535	-10.381	6	-31.233	0.049
Nikkei Stock Average 225	-1.456	0	-1.552	2.938	-6.166	21	-34.075	0.072
Taiwan's Composite index	-3.017	0	-3.356	0.408	-8.528	10	-30.901	0.133
Bombay SE Sensitive index	0.446	0	0.306	2.296	-5.607	21	-29.606	0.123

Note: Test critical values:		ADF	PP-TEST	KPSS
	1% level	-3.4361	-3.43609	0.739
	5% level	-2.86397	-2.86397	0.463
	10% level	-2.56811	-2.56811	0.347

Critical values in the table from EViews 6.

Table 3: Tse test from CCC model

Asia Stock Indexes	Test Statistic
All Ordinaries index	3.376*
KLSE Composite index	1.962
Nikkei Stock Average 225	6.512**
Taiwan Composite index	3.391*
Bombay SE Sensitive index	1.308

Note: There are 2 degrees of freedom and m = 1

*, ** and *** indicate significance at the 0.10, 0.05 and 0.01 levels, respectively.

The bivariate GARCH model with constant correlation is fitted to the log returns of all stock index and log returns of Singapore gasoline price, the estimated correlations between the log returns of stock index are much low. The values of correlation are zero. However, the LM statistic of testing for constant correlation of KLSE (KLSE Composite index), Malaysian stock market, The BSESN (Bombay SE Sensitive index) Bombay Stock Exchange is all in the region of 1.962 to 1.308. It is asymptotically distributed as a $\chi 2$, where M = 1 for K= 2 indicates statistical significance at the 10% level. Thus, there is no evidence against time-invariant correlations. These results have low correlations and/or their relationships stable over time, they show the correlations of market returns and log returns of Singapore gasoline price to be not time varying.

The results for Nikkei 225 (Nikkei Stock Average 225), Tokyo Stock Exchange, TWSE (Taiwan's composite index), Taiwan Stock Exchange, The ALL (ASX All Ordinaries index) are strong evidence (at the 10% level) of time-varying correlations them and bivariate case. The LM statistics of testing for constant correlation are all in the region of 3.376 to 6.512. The log returns of stock index are dependent on log returns of Singapore gasoline price factors. These factor has low correlations and/or their relationships are not stable over time, we would expect the correlations of market returns to be time varying.

In addition to estimating the conditional mean for each index, the VARMA-GARCH models are used to estimate the conditional volatility associated with the log returns of all stock index. On the basis of the univariate standardised shocks, the two multivariate models are used to estimate the conditional correlation coefficients of the weekly index return shocks between the log returns of all stock index and log returns of Singapore gasoline price. This can provide useful information regarding the relationship between the indexes in terms of the shocks to index returns. In this paper, the estimates of the parameters are obtained using the Berndt, Hall, Hall and Hausman (BHHH) (1974) in the RATS 6 econometric package.

Table 4 reports the estimates of the DCC, VARMA-GARCH (Ling, S., and M. McAleer, 2003, McAleer, 2005) model. The estimation use bivariate GARCH model, which included oil price rates of return with each rates of return of the index in the Asian market. The paper wants to investigate the effect of oil price rates of return to each market in Asian stock market. The results show significant dynamics for the log returns of all stock index and log returns of Singapore gasoline price, except for the BSESN (Bombay SE Sensitive index) Bombay Stock Exchange. On the other hand, The BSESN (Bombay SE Sensitive index) Bombay Stock Exchange are not affected to log returns of Singapore gasoline price by non significance dynamic conditional correlation equation while the others indexes have affected to dynamic conditional correlation equation.

The estimates of the conditional variance for the log returns of all stock index and log returns of Singapore gasoline price show that the BSESN (Bombay SE Sensitive index) Bombay Stock Exchange is affected by its own previous short run ARCH parameters at lag{1}(1,1) , ARCH parameters at lag{1}(2,2) , ARCH parameters at lag{2}(1,1) , ARCH parameters at lag{2}(2,2) , and long run GARCH parameters at lag{1}(2,2) shocks. The BSESN (Bombay SE Sensitive index) Bombay Stock Exchange has not dynamic conditional correlation. The evidences show in testing for constant correlations in a multivariate GARCH model and estimates of DCC, VARMA-GARCH model. It has only own effects in terms of long run shocks and short run shocks.

The ALL (ASX All Ordinaries index), Nikkei 225 (Nikkei Stock Average 225), Tokyo Stock Exchange, TWSE (Taiwan's composite index), Taiwan Stock Exchange shows that there are effects between the log returns of each stock index and log returns of Singapore gasoline price.

Using the standardized residuals, table 5 we obtain the Ljung–Box statistics and the squared standardized residuals show that at the 5% significance level, the standardized residuals at have no serial correlations or conditional heteroscedasticities. This bivariate GARCH(2,1) model shows a feedback relationship between the volatilities of the log returns.

The fitted conditional correlation coefficient are captured them by nonlinear approach. LSTAR (Logistic Smooth Threshold Autoregressive model) and SETAR (Self Exciting Threshold Autoregressive model) models are proposed to capture the patterns. The selecting models depend on The Pooled AIC (Philip Hans Franses, 2004). The package TsDyn in software R is very useful for this area (Antonio, 2007).

Table 6 shows the result of LSTAR (Logistic Smooth Threshold Autoregressive model). The smooth transition conditional correlation model considered by Silvennoinen and Terasvirta (2005) assumes the presence of two extreme states (or regimes) with state-specific constant correlations. The gamma value of models are all in the region of -70.734

to 0.546, the model of The Nikkei 225 (Nikkei Stock Average 225), Tokyo Stock Exchange, the TWSE (Taiwan's composite index), Taiwan Stock Exchange, the BSESN (Bombay SE Sensitive index) Bombay Stock Exchange are not significant.

Table 4: Logarithmic Returns of Asian Stock Indexes and Singapore Gasoline in the Dynamic Conditional Correlation (DCC) model

Parameter	All Ordinaries Index		KLSE Composite Index		Nikkei 225		Taiwan's Composite Index		Bombay SE Sensitive Index	
	Coefficient	**Std Error**	**Coefficient**	**Std Error**	**Coefficient**	**Std Error**	**Coefficient**	**Std Error**	**Coefficient**	**Std Error**
Constant Returns Stock Indexes	0.224	0.052***	0.156	0.067**	-0.004	0.083	0.168	0.099*	0.391	0.109***
Returns Stock Indexes{1}	0.033	0.046	0.115	0.031***	-0.007	0.032	0.043	0.031	-	-
Returns Stock Indexes{2}	-	-	-	-	-	-	0.032	0.032	-	-
Returns Stock Indexes{3}	-	-	-	-	-	-	0.081	0.031***		
Constants Singapore Gasoline	0.099	0.074	0.084	0.078	-0.052	0.065	0.118	0.081	0.178	0.096**
Singapore Gasoline{1}	0.325	0.035***	0.325	0.034***	0.359	0.032***	0.364	0.038***	-	-
Singapore Gasoline{2}	-	-	-	-	-	-	-0.102	0.032***	-	-
Singapore Gasoline{3}	0.099	0.028***	0.1	0.029***	-	-	0.137	0.030***	-	-
Bivariate GARCH Equation										
Constants bivariate GARCH at Equation 2	0.145	0.058**	0.101	0.035***	0.492	0.146***	0.331	0.088***	1.541	0.577***
Constants bivariate GARCH at Equation 2	0.128	0.042***	0.098	0.044**	0.15	0.039***	0.141	0.041***	0.062	0.083
ARCH parameters at lag 1(1,1)	0.367	0.033***	0.12	0.034***	0.078	0.035**	0.084	0.035**	-0.197	0.042***
ARCH parameters at lag 1(1,2)	0.068	0.021***	-0.034	0.03	-0.045	0.036	0.019	0.051	2.827	1.264
ARCH parameters at lag 1(2,1)	-0.013	0.08	-0.026	0.039	-0.171	0.043***	0.001	0.015	-1.884	2.276
ARCH parameters at lag 1(2,2)	0.287	0.037***	0.263	0.041***	0.216	0.041***	0.358	0.047***	0.939	0.109***
ARCH parameters at lag 2(1,1)	-0.253	0.047***	-0.008	0.037	-0.005	0.043	0.025	0.039	0.767	0.039***
ARCH parameters at lag 2(1,2)	-0.076	0.029***	0.009	0.028	-0.033	0.04	0.119	0.057**	2.251	1.039**
ARCH parameters at lag 2(2,1)	-0.1	0.074	0.012	0.05	0.072	0.046	0.018	0.022	2.586	2.05*
ARCH parameters at lag 2(2,2)	-0.189	0.039***	-0.161	0.043***	-0.129	0.042***	-0.254	0.049***	-0.044	0.089***
GARCH parameters at lag 1(1,1)	0.873	0.036***	0.893	0.014***	0.872	0.035***	0.899	0.017***	0.137	0.022***
GARCH parameters at lag 1(1,2)	0.067	0.081	0.075	0.045*	0.096	0.041**	-0.663	0.224***	-0.034	0.035**
GARCH parameters at lag 1(2,1)	0.446	0.278	-0.051	0.092	0.187	0.072***	-0.167	0.084**	0.054	0.052
GARCH parameters at lag 1(2,2)	0.906	0.012***	0.897	0.013***	0.916	0.012***	0.904	0.013***	0.370	0.046***
GARCH parameters at lag 2(1,1)	-	-	-	-	-	-	-	-	0.104	0.024***
GARCH parameters at lag 2(2,1)	-	-	-	-	-	-	-	-	-0.093	0.045**
GARCH parameters at lag 2(2,1)	-	-	-	-	-	-	-	-	-0.093	0.051
GARCH parameters at lag 2(2,2)	-	-	-	-	-	-	-	-	-0.273	0.047
DCC parameter 1	0.044	0.035	0.052	0.031*	0.02	0.008**	0.058	0.030*	0.017	0.009
DCC parameter 2	0.782	0.135***	0.82	0.104***	0.961	0.011***	0.579	0.172***	0.544	0.138

Note : Stock Returns Indexes {i} is lag time of the Stock Returns Indexes at i, and ARCH parameters at lag i(j,k) is lag time i and row j, column k

* ,** and *** indicate significance at 0.10 ,0.05 and 0.01 levels, respectively.

Using the standardized residuals, table 7 we obtain the Ljung–Box statistics and the squared standardized residuals show that at the 5% significance level, the standardized residuals at have no serial correlations or conditional heteroscedasticities in this LSTAR (Logistic Smooth Threshold Autoregressive model) bivariate GARCH(2,1). Because of inappropriate gamma values, The SETAR (Self Exciting Threshold Autoregressive model) models are considered to capture the patterns. The pooled AIC which show in R software are presented the parsimonious model in Table 8. The threshold delay, threshold values, low regimes autoregressive orders and high regimes autoregressive orders show the least pooled AIC of each model for determining parameters of each model by RATS software which calculated them in BHHH Method.

Table 5: Multivariate Portmanteau Tests

The Stock Indexes	Serial Correlation test		Heteroscedasticity test	
	Test-Statistic	prob	Statistic	prob
All Ordinaries Index	31.803	0.329	13.202	0.992
KLSE Composite Index	26.850	0.580	14.651	0.982
Nikkei 225	34.760	0.213	35.835	0.147
Taiwan's Composite Index	31.807	0.328	22.816	0.742
Bombay SE Sensitive Index	30.913	0.370	73.306	0.000

Table 6: Logarithmic Returns of Asian Stock Indexes and Singapore Gasoline in the STAR Dynamic Conditional Correlation (DCC) Model

Parameter	All Ordinaries Index		KLSE Composite Index		Nikkei 225		Taiwan's Composite Index		Bombay SE Sensitive Index	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Constants Returns Stock Indexes	0.283	0.047***	0.154	0.064**	0.021	0.069	0.216	0.028***	0.313	0.113***
Returns Stock Indexes{1}	0.006	0.035	0.104	0.031***	-0.014	0.034	0.065	0.022***	0.082	0.034**
Returns Stock Indexes{2}	-	-	-	-	-	-	0.025	0.018	0.033	0.032
Returns Stock Indexes{3}	-	-	-	-	-	-	0.074	0.024***	0.038	0.031
Constants Singapore Gasoline	0.081	0.076	0.063	0.081	0.136	0.082*	0.131	0.009***	0.265	0.095***
Singapore Gasoline{1}	0.334	0.029***	0.338	0.030***	0.343	0.031***	0.316	0.019***	0.316	0.036***
Singapore Gasoline{2}	-	-	-	-	-	-	-0.062	0.024***	-0.008	0.039
Singapore Gasoline{3}	0.109	0.028***	0.108	0.028***	-	-	0.136	0.028***	0.115	0.031***
Constants bivariate GARCH at Equation 2	0.402	0.148***	0.126	0.044***	1.090	0.055***	0.101	0.000***	0.298	0.131**
Constants bivariate GARCH at Equation 2	0.208	0.087**	0.133	0.086	0.440	0.037***	0.669	0.043***	0.247	0.245
Bivariate GARCH Equation										
ARCH parameters at lag 1(1,1)	0.148	0.027***	0.112	0.010***	0.050	0.009***	0.129	0.006***	501.731	493.375
ARCH parameters at lag 1(1,2)	0.142	0.002***	-0.141	0.002***	-0.178	0.004***	-0.099	0.0004***	-5.449	-0.017***
ARCH parameters at lag 1(2,1)	0.084	0.012***	0.139	0.004***	0.110	0.004***	0.120	0.002***	337.244	1479.115
ARCH parameters at lag 1(2,2)	0.081	0.012***	0.043	0.012***	0.095	0.008***	0.136	0.007***	749.077	0.033***
ARCH parameters at lag 2(1,1)	0.167	0.027***	0.006	0.010	0.073	0.009***	0.048	0.006***	-501.629	493.374
ARCH parameters at lag 2(1,2)	-0.144	0.002***	0.137	0.002***	0.197	0.004***	0.077	0.0004***	5.445	0.000***
ARCH parameters at lag 2(2,1)	-0.086	0.012***	-0.142	0.004***	-0.090	0.004***	-0.111	0.002***	-337.256	1479.120
ARCH parameters at lag 2(2,2)	0.073	0.012***	0.100	0.012***	0.101	0.008***	0.067	0.007***	-748.799	0.000***
GARCH parameters (1,1)	0.662	0.064***	0.885	0.017***	0.734	0.012***	0.819	0.004***	0.836	0.010***
GARCH parameters (1,2)	0.001	0.004	0.000	0.004	-0.012	0.000***	0.043	0.002***	0.051	0.017***
GARCH parameters (2,1)	0.002	0.003	0.011	0.006*	-0.035	0.008***	-0.005	0.002***	0.077	0.022***
GARCH parameters (2,2)	0.843	0.022***	0.850	0.022***	0.799	0.007***	0.742	0.005***	0.665	0.030***
Nonlinear STAR DCC										
upper Constant DCC Parameters	-2.657	-0.008***	-93.317	945.784	-73.906	127.478	326.337	16526.432	2692.058	3377.255
upper DCC Parameters 1	-69.687	-0.539***	-8852.997	38083.994	-140928.446	193158.219	20573.335	1397827.652	-32106.141	28315.426
upper DCC Parameters 2	-0.515	0.056***	7.039	139.725	19.615	32.534	-101.151	4033.499	666.181	1414.625
lower Constant DCC Parameters	3.279	1.954*	-515.405	297.114*	-134.853	105.086	-25.928	9.790***	-1480.564	1849.420
lower DCC Parameters 1	-18.952	30.840	-8877.073	38295.839	-116849.744	172168.301	-63132.090	254726.192	16134.283	15689.797
lower DCC Parameters 2	-2.143	1.186*	73.514	42.943*	-4.137	14.692	4.765	1.858**	-365.664	775.226
Gamma	-8.570	4.321**	-9.927	4.213**	-70.734	115.820	-10.005	640.123	0.546	0.461
Threshold	5.415	2.313**	4.865	1.552***	-9.435	15.472	-70.248	4475.747	1.102	0.931

Note: Stock Returns Indexes {i} is lag time of the Returns Stock Indexes at i, and ARCH parameters at lag i(j,k) is lag time i and row j, column k

Table 7: Multivariate Portmanteau Tests

The Stock Indexes	Serial Correlation test		Heteroscedasticity test	
	Test-Statistic	prob	Statistic	prob
All Ordinaries Index	31.231	0.404	14.409	0.954
KLSE Composite Index	26.302	0.660	25.531	0.433
Nikkei 225	31.779	0.378	29.937	0.227
Taiwan's Composite Index	30.799	0.425	26.060	0.404
Bombay SE Sensitive Index	26.117	0.669	29.415	0.247

Table 8: Threshold delay and values, Low and High Regimes AR Orders, Pooled AIC in SETAR Model

	Threshold Delay	Threshold Values	Low Regimes AR Orders	High Regimes AR Orders	Pooled.AIC
All Ordinaries Index	1	-0.0610	2	1	-4541.30
KLSE Composite Index	0	-0.1062	1	1	-4180.95
Nikkei 225	0	-0.0533	1	1	-5882.15
Taiwan's Composite Index	1	0.0681	2	2	-3754.80
Bombay SE Sensitive Index	0	0.0184	2	2	-3916.54

Table 9: Conditional correlation in SETAR Model

Threshold	All Ordinaries Index		KLSE Composite Index		Nikkei 225		Taiwan Composite Index		Bombay SE Sensitive Index	
	-0.0525		-0.1063		-0.0719		0.0515		0.0213	
Variable	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
PLUS	-0.0009	0.0011	-0.0083	0.0015***	-0.0014	0.0006**	0.0033	0.005	0.0259	0.0019
Y1_PLUS	0.7354	0.0439***	0.8284	0.0256***	0.9745	0.0161***	0.8729	0.0498***	-0.0794	0.0546
Y2_PLUS	0.0464	0.0408	-	-	-	-	-0.1808	0.0437***	-0.0051	0.0476***
MINUS	-0.0085	0.0045*	0.0168	0.0052***	0.0033	0.0017**	0.0129	0.0017***	-0.1263	0.0403***
Y1_MINUS	0.84	0.0348***	1.0043	0.0207***	1.0022	0.0075***	0.6558	0.0474***	0.0204	0.0011
Y2_MINUS	-	-	-	-	-	-	-0.0148	0.0421	0.052	0.0518

Table 9 presents The SETAR (Self Exciting Threshold Autoregressive model) model of each stock market. The threshold values are all in the region of -0.1062 to 0.0681. The SETAR (Self Exciting Threshold Autoregressive model) models show the significant variable and minima lag length. The significance at 0.01 minima lag length equal one in each model. The maxima of lag length in model equal lag three in conditional correlation coefficient of The BSESN (Bombay SE Sensitive index) Bombay Stock Exchange model and significance at 0.01.

3.5 Conclusion

This research shows model of univariate volatility and bivariate volatility in VARMA-GARCH model (Ling, S., and M. McAleer, 2003). The Singapore oil price in log return is presented that It has time-varying correlations in dynamic conditional correlation with the others log return of Asia stock index. The time-varying correlations in dynamic conditional correlation multivariate model DCC, the regime-switching SETAR (Self Exciting Threshold Autoregressive model) and smooth transition conditional correlation model, LSTAR (Logistic Smooth Threshold Autoregressive model) are presented in the paper.

The testing for the constant-correlation hypothesis based on the Lagrange Multiplier (LM) approach in Journal of econometrics (Tse.Y.K., 2000) found that the KLSE (KLSE Composite index), Malaysian stock market, the BSESN (Bombay SE Sensitive index) Bombay Stock Exchange indicates statistical significance at the 10% level. Thus, there is no evidence against time-invariant correlations. These results have low correlations and/or their relationships stable over time, they show the correlations of market returns and log returns of Singapore gasoline price to be not time varying. The results for Nikkei 225 (Nikkei Stock Average 225), Tokyo Stock Exchange, TWSE (Taiwan's composite index), Taiwan Stock Exchange, ALL (ASX All Ordinaries index) have time-varying correlations them and bivariate case. The log returns of stock index has low correlations and/or their relationships are not stable over time, we would expect the correlations of market returns to be time varying.

The VARMA-GARCH models are used to estimate the conditional volatility associated with the log returns of all stock index. The estimates of the parameters are obtained using the Berndt, Hall, Hall and Hausman (BHHH) (1974) in the RATS 6 econometric package. The results show significant dynamics for the log returns of all stock index and log returns of Singapore gasoline price, except for the BSESN (Bombay SE Sensitive index) Bombay Stock Exchange. On the other hand, The BSESN (Bombay SE Sensitive index) Bombay Stock Exchange are not affected to log returns of Singapore gasoline price by non significance dynamic conditional correlation equation while the others indexes have affected to dynamic conditional correlation equation.

The fitted conditional correlation coefficient looks like nonlinear form. This paper tries to capture them by nonlinear approach. LSTAR (Logistic Smooth Threshold Autoregressive model) and SETAR (Self Exciting Threshold Autoregressive model) models are proposed to capture the patterns. The selecting models depend on The Pooled AIC (Philip Hans Franses, 2004) by using the package TsDyn in software R (Antonio, 2007). The gamma value of model of The Nikkei 225 (Nikkei Stock Average 225), Tokyo Stock Exchange, the TWSE (Taiwan's composite index), Taiwan Stock Exchange, the BSESN (Bombay SE Sensitive index) Bombay Stock Exchange are not significant. The SETAR (Self Exciting Threshold

Autoregressive model) models are considered to capture the patterns. The pooled AIC which show in R software are presented the parsimonious model. The threshold values are all in the region of -0.1062 to 0.0681. The SETAR (Self Exciting Threshold Autoregressive model) models show the significant variable and minima lag length. The maxima of lag length in model equal lag two in conditional correlation coefficient of The BSESN (Bombay SE Sensitive index) Bombay Stock Exchange model and significance at 0.01. The significance at 0.01 minima lag length equal one in each model.