APPENDIX

Thailand Econometrics Society, Vol. 1, No. 1 (January 2009), 211 - 222

The Effects of Oil Prices on Asia Stock Indexes

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ARTICLE INFO

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

JEL classification codes:
C22, C32, G17, G32, Q43.

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.

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

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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.

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

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

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

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

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

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

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

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

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

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

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

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

$$LMC = \hat{s}'\left(\hat{S}'\hat{S}\right)^{-1}\hat{s} \quad (8)$$
$$= l'\hat{S}\left(\hat{S}'\hat{S}\right)^{-1}\hat{S}'l, \quad (9)$$

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.

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

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

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

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

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. Data and Estimation

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)

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 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

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.

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 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.

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 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 *	0.457	0.126***
Returns Stock Indexes{1}	0.033	0.046	0.115	0.031 ***	-0.007	0.032	0.043	0.031	0.062	0.038
Returns Stock Indexes{2}	-	-	-	-	-	-	0.032	0.032	0.078	0.038**
Returns Stock Indexes{3}	-	-	-	-	-	-	0.081	0.031***	0.070	0.026***
Constants Singapore Gasoline	0.099	0.074	0.084	0.078	-0.052	0.065	0.118	0.081	0.106	0.091
Singapore Gasoline{1}	0.325	0.035***	0.325	0.034***	0.359	0.032***	0.364	0.038***	0.335	0.032***
Singapore Gasoline{2}	-	-	-	-	-	-	-0.102	0.032***	0.041	0.040
Singapore Gasoline{3}	0.099	0.028***	0.100	0.029***	-	-	0.137	0.030***	0.032	0.032
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***	12.219	1.604***
Constants bivariate GARCH at Equation 2	0.128	0.042***	0.098	0.044**	0.150	0.039***	0.141	0.041***	1.297	0.395***
ARCH parameters at lag 1(1,1)	0.367	0.033***	0.120	0.034***	0.078	0.035**	0.084	0.035**	0.114	0.028***
ARCH parameters at lag 1(1,2)	0.068	0.021***	-0.034	0.030	-0.045	0.036	0.019	0.051	0.045	0.059
ARCH parameters at lag 1(2,1)	-0.013	0.080	-0.026	0.039	-0.171	0.043***	0.001	0.015	0.051	0.036
ARCH parameters at lag 1(2,2)	0.287	0.037***	0.263	0.041***	0.216	0.041***	0.358	0.047***	0.147	0.028***
ARCH parameters at lag 2(1,1)	-0.253	0.047***	-0.008	0.037	-0.005	0.043	0.025	0.039	0.109	0.044**
ARCH parameters at lag 2(1,2)	-0.076	0.029***	0.009	0.028	-0.033	0.040	0.119	0.057**	0.002	0.117
ARCH parameters at lag 2(2,1)	-0.100	0.074	0.012	0.050	0.072	0.046	0.018	0.022	0.008	0.101
ARCH parameters at lag 2(2,2)	-0.189	0.039***	-0.161	0.043***	-0.129	0.042***	-0.254	0.049***	0.190	0.054***
GARCH parameters (1,1)	0.873	0.036***	0.893	0.014***	0.872	0.035***	0.899	0.017***	-0.003	0.098
GARCH parameters (1,2)	0.067	0.081	0.075	0.045*	0.096	0.041**	-0.663	0.224***	0.117	1.773
GARCH parameters (2,1)	0.446	0.278	-0.051	0.092	0.187	0.072***	-0.167	0.084**	-0.025	2.583
GARCH parameters (2,2)	0.906	0.012***	0.897	0.013***	0.916	0.012***	0.904	0.013***	0.581	0.053***
DCC parameter 1	0.044	0.035	0.052	0.031*	0.020	0.008**	0.058	0.030*	0.044	0.036
DCC parameter 2	0.782	0.135***	0.820	0.104***	0.961	0.011***	0.579	0.172***	0.000	0.729

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.

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.

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.

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Thailand Econometrics Society, Vol. 1, No. 1 (January 2009), 77 - 96

Semi Parametric Estimation of ARFIMA Models of Asian Stock Indexes

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ARTICLE INFO

Keywords:
ARFIMA, SEMIFAR, Long memory fractional.
JEL classification codes:
C32; G11; G32

ABSTRACT

The long memory process can provide a good description of many highly persistent financial time series. The log daily Asia prices Index from November 10, 1998 to November 10, 2008 are highly persistent and remains very significant in the autocorrelation function. The R/S statistic and GPH test confirm the long memory property. The BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange with slop of the linear trend, N225 (Nikkei Stock Average 225) Tokyo Stock Exchange, PSI (PSE Composite Index) Philippine Stock Exchange are stationary and short memory. The SSEC (Shanghai Composite Index) Shanghai Stock Exchange, JKSE (Jakarta Composite) Indonesia Jakarta Composite, KLSE (KLSE Composite Index) Malaysian stock market, SETI (SET Composite Index) the Stock Exchange of Thailand, KS11 (KOSPI Index) Korean Stock Exchange, TWSE (Taiwan's composite index) Taiwan Stock Exchange are stationary and long memory. The ACF plot of all log price Asia Indexes have been well capture by the SEMIFAR model which is replaced μ by $g(i_t)$, a smooth trend. The graph contains the predicted values, standard errors of predictions and generating coefficient plot of the coefficient are not change the prediction.

1. Introduction

There is a lot of money flowing into international funds and especially in Asia during 2007. In the last several years, the Chinese markets have jumped overnight, with the Shanghai Composite Index down 6.5% and the smaller Shenzhen Composite Index down 7.2%. Five million new Chinese brokerage accounts were opened in April, two-thirds more than during last year 2006 in total. Volumes in Asian stock markets are increasing at an unprecedented rate, with trading volume on the Chinese markets at $16.4 billion a day in March of this year, while six months prior it was only $5 billion a day. The total number of shares traded on China's stock market was greater than the combined volume of all other Asia exchanges. This includes Japan, Hong Kong, Thailand, and Singapore. In

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April 2003 to April 2007, the MSCI Asia Pacific Price Index is up a whopping 148.15%, annualizing 24.93%. The Hang Seng Index in Hong Kong is up 135.33% over the same time period, annualizing 23.32%. The Shanghai Stock Exchange is up 154.18%, annualizing at 25.67%. India is even more impressive, up 317.91% in the Nifty 50, which comes to a 41.94% annualized return (Sundt, 2007). The last year 2008, financial crisis in Asia suffers further stock market slide. The Tokyo's Nikkei 225 average drowns continuing. It is the lowest level since May 2003. It has lost half its value this year. The carry trades that have depressed the currency for years are unwinding, with the yen rising to a 13-year high against the dollar. The Korea Exchange temporarily halted trading for the 11th time this year to break a run on index futures. The falls followed third quarter growth figures showing the economy expanded 3.9 percent, the slowest since 2005 (Spencer, 2008).

From the uncertain situation, the many economic and financial time series lie on the borderline separating stationary from non-stationary. The ARFIMA model has become a tool in the analyses of time series in different fields such as economic time series, astronomy, hydrology, computer science and many others. It can characterize "long-range dependence or positive memory" when d lies (0.0, 0.5), and "intermediate or negative memory" when d lies (−0.5, 0.0). A good review of long memory process may be found in Beran (Sowel, 1992) and(Beran J. , 1994). Focusing on non- and semi-parametric methods is on modelling and forecasting using methods based on maximum likelihood and regression for the Gaussian fractionally integrated ARMA model (ARFIMA). This allows flexible modelling of the long-run behavior of the series, and often provides a good description for forecasting. There are many estimators of the parameter d. They are grouped mainly into two categories: The parametric and semiparametric methods. The semiparametric estimation methods (those of Geweke and Porter-Hudak (Geweke, 1983), (Lobato, 1996) and (John G. W., 2001)) recommend that provided the correct ARFIMA model is fitted the ML procedure is probably superior to the GPH and APER procedures.

The outline of this paper is as follows: in Section 2 we summarize some results related to the ARFIMA (p, d, q) model SEMIFAR and the estimation of the parameters of this process(Valderio A. R., 2000), (Doornik L.A., 2004) and(Zivot., 2006) . Section 3 we show model over view for estimation of coefficients. In Section 4, long memory and short memory models are used to forecasting. The concluding is given in Section 5.

2. Model Specifications

Long Memory Time Series

A stationary process y_t has long memory, or long range dependence, if its autocorrelation function behaves like

$$\rho(k) \to C_\rho k^{-\alpha} \text{ as } k \to \infty \qquad (2.1)$$

where C_ρ is a positive constant, and α is a real number between 0 and 1. Thus the autocorrelation function of a long memory process decays slowly at a hyperbolic rate. In fact, it decays so slowly that the autocorrelations are not summable:

$$\sum_{k=-\infty}^{\infty} \rho(k) = \infty$$

For a stationary process, the autocorrelation function contains the same information as its spectral density. In particular, the spectral density is defined as:

$$f(\omega) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \rho(k) e^{ik\omega}$$

Where ω is the Fourier frequency (Halmilton, 1994). From (2.1) it can be shown that

$$f(\omega) \to C_f \omega^{\alpha-1} \text{ as } \omega \to 0 \qquad (2.2)$$

where C_f is a positive constant. So for a long memory process, its spectral density tends to infinity at zero frequency. Instead of using α, in practice use

$$H=1-\alpha/2\in(0.5,1), \quad (2.3)$$

Which is known as the Hurst coefficient (Hurst, 1951) to measure the long memory in y_t. The larger H is the longer memory the stationary process has.

Based on the scalling property in (2.1) and the frequency domain property in (2.2), Hosking (Hosking, 1981) independently showed that a long memory process y_t can also be modeled parametrically by extending an integrated process to a fractionally integrated process. In particular, allow for fractional integration in a time series y_t as follow:

$$(1-L)^d(y_t-\mu)=u_t \quad (2.4)$$

where L denotes the lag operater , d is the fractional integration or fractional difference parameter , μ_t is a stationary short-memory disturbance with zero mean.

The time series is highly persistent or appears to be non-stationary, let d = 1 and difference the time series once to achieve stationarity. However, for some highly persistent economic and financial time series, it appear that an integer difference may be too much, which is indicated by the fact that spectral density vanishes at the zero frequency for the differenced time series. To allow for long memory and avoid taking an integer of y_t, allow d to be fractional. The fractional difference filter is defined as follows, for any real d > -1:

$$(1-L)^d=\sum_{k=0}^{\infty}\binom{d}{k}(-1)^k L^k \quad (2.5)$$

with binomial coefficients:

$$\binom{d}{k}=\frac{d!}{k!(d-k)!}=\frac{\Gamma(d+1)}{\Gamma(k+1)\Gamma(d-k+1)}$$

Notice that the fractional difference filter can be equivalent treated as an infinite order autoregressive filter. It can be show that when $|d|>1/2$, y_t is stationary and has short memory , and is sometimes refer to as anti-persistent.

When a fractionally integrated series y_t has long memory, it can also be shown that

$$d=H-1/2 \quad (2.6)$$

and thus d and H can be used interchangeably as the measure of long memory. Hosking(1981) showed that the scaling property in (2.1) and the frequency domain property in (2.2) are satisfied when $0<d<1/2$.

ARFIMA models

The traditional approach to modeling an I(0) time series y_t is to use the ARIMA model:

$$\varphi(B)(1-B)^d\{y_t-\mu\}=\theta(B)\in_t \quad (2.7)$$

Where $\varphi(B)$ and $\theta(B)$ are lag polynomials

$$\varphi(B)=1-\sum_{i=1}^{p}\varphi_i B^i$$

$$\theta(B)=1-\sum_{j=1}^{q}\theta_j B^{ji}$$

With root out side the unit circle, and $\in_t$ is assumed to be an i.i.d normal random variable .this is usually referred to as the ARMA (p,d,q) model. By allow d to be the real number instead of a positive integer, the ARIMA model becomes the Autoregressive fractionally integrated moving average (ARFIMA) model. The stationary FARIMA model is -1/2<d<1/2,(Sowel, 1992). The ARFIMA or FARIMA was extended by Beran (Beran j. , 1995).

$$\varphi(B)(1-B)^\delta\{(1-B)^m y_t-\mu\}=\theta(B)\in_t \quad (2.8)$$

where δ , -1/2< δ<1/2 and m is the number of times that y_t must be differenced to achieve stationarity. The difference parameter is given by d = δ+m. The restriction of m is either 0 or 1 , when m=0, μ is the expectation of y_t; in contrast, when m=1, μ is the slop of the linear trend component in y_t.

SEMIFAR models

Many observed time series exhibit apparent trends. Forecasts will differ greatly, depending on how these trends are modelled. A trend may be deterministic, i.e. defined by a deterministic function and purely stochastic or mixture of both.
SEMIFAR models are define by (Beran J. A., 1999): A *Gaussian process* Y_i *is called* a semiparametric fractional autoregressive model (*or* SEMIFAR *model*) *or order p , if there exists a smallest integer* $m \in \{0,1\}$ such that

$$\varphi(B)(1-B)^{\delta}\{(1-B)^{m} Y_i - g(t_i)\} = \in_i \quad (2.9)$$

where $\delta \in (-0.5, 0.5)$.
Estimation for SEMIFAR model Let

$$\theta^{o} = \left(\sigma^2_{\in,o}, d^{o}, \phi_1^{o}, \dots, \phi_p^{o}\right)^t = \left(\sigma^2_{\in,o}, \eta^{o}\right)^t$$

be the true unknown parameter vector in (2)where
$d^0 = m^0 + \delta^0, -1/2 < \delta^0 < 1/2 \; and \; m^0 \in \{0,1\}$.
Combining maximum likelihood with kernel estimation , the following method for estimating θ^0 and the trend function g is obtained in (Beran J. A., 1999): Let K be a symmetric polynomial kernel define by
$K(x) = \sum_{l=0}^{r} \alpha_l x^{2l}, |x| \le 1, \; and \; K(x) = 0 \; if \; |x| > 1,$
$r \in \{0,1,2,\dots\}$, and $K(x) = 0 \; if \; |x| > 1$, $r \in \{0,1,2,\dots\}$ and the coefficient α_l such that $\int_{-1}^{1} K(x)dx = 1$. Let $b_n (n \in N)$ be a sequence of positive bandwidths such that $b_n \to 0$ and $nb_n \to \infty$ and define $\hat{g}(t_i) = \hat{g}(t_i; m)$ by

$$\hat{g}(t_i; m) = \frac{1}{nb_n} \sum_{j=1}^{n} K\left(\frac{t_i - t_j}{b_n}\right) \tilde{Y}_j \quad (2.10)$$

where
$\tilde{Y}_j = (1-B)^m Y_j$ (for $m = 1, set \; \tilde{Y}_1 = 0$).
Using equations (2.9) and (2.10), define approximate residuals

$$e_i(\eta) = \sum_{j=0}^{i-m-1} a_j(\eta)[c_j(\eta) Y_{i-j} - \hat{g}(t_{i-j}; m)], \quad (2.11)$$

With coefficient a_j and c_j obtained from (2.9), and denote by $r_i(\theta) = e_i(\eta)/\sqrt{\theta_1}$ the standardized residual as a function of a trial value $\theta = \left(\sigma^2_{\in}, m+\delta, \phi_1, \dots, \phi_p\right)^t$. Then $\hat{\theta}$ is defined by maximizing the approximate log-likelihood

$$l(Y_1,\dots,Y_n;\theta) = -\frac{n}{2}\log 2\pi - \frac{n}{2}\log \sigma^2_{\in} - \frac{1}{2} n^{-1} \sum_{i=m+2}^{n} r_i^2 \quad (2.12)$$

with respect to θ and $\hat{g}(t_i)$ is set equal to $\hat{g}(t_i; \hat{m})$.

The asymptotic behavior of $\hat{g}$ and $\hat{\theta}$ is derived in Beran(1999). As $n \to \infty$, $\hat{g}$ converges in probability to g , the optimal mean squared error of $\hat{g}$ is proportional to $n^{(4\delta - 2)/(5 - 2\delta)}$ and $\sqrt{n}(\hat{\theta} - \theta)$ converges in distribution to a zero mean normal vector with covariance matrix $V = 2D^{-1}$ where

$$D_{ij} = (2\pi)^{-1} [\int_{-\pi}^{\pi} \frac{\partial}{\partial \theta_i} \log f(x) \frac{\partial}{\partial \theta_j} \log f(x) dx] \Big| \theta = \theta_*^{O} \quad (2.13)$$

with $\theta_*^{o} = \left(\sigma^2_{\in,o}, \eta_*^{o}\right)^T = \left(\sigma^2_{\in,o}, \delta^{o}, \eta_2^{o}, \dots, \eta_{p+1}^{o}\right)^T$.
The same result hold if a consent model choice criterion is used for the estimation of the autoregressive order *p*.It should be emphasized , in particular , that here both , the integer differencing parameter $m^o = [d^o + 0.5]$ and the fractional differencing parameter $\delta^o = d^o - m^o$ are estimated from the data. Also, the same central limit theorem holds if the innovation $\in_i$ are not normal, and satisfy suitable moment conditions. Finally note that the asymptotic covariance matrix does not depend on m^o

R/S Statistic

The R/S statistic is the range of partial sum of deviation of a time series from its mean, rescaled by its standard deviation. Specifically, consider a time series series y_t for $t = 1,...,T$. The R/S statistic is defined as:

$$Q_T = \frac{1}{s_T}\left[\max_{1\le k\le T}\sum_{j=1}^{k}(y_j - \bar{y}) - \min_{1\le k\le T}\sum_{j=1}^{k}(y_j - \bar{y})\right] \quad (2.14)$$

where $\bar{y} = 1/T\sum_{i=1}^{T} y_i$ and $s_T = \sqrt{1/T\sum_{i=1}^{T}(y_i - \bar{y})^2}$. If y_t's are i.i.d. normal random variables, then

$$\frac{1}{\sqrt{T}} Q_T \Rightarrow V$$

where $\Rightarrow$ denote weak convergence and V is range of a Brownian bridge on the unit interval. Lo(1991) gives selected quantiles of V

Lo(1991) pointed out that the R/S statistic is not robust to short range dependence. In particular, if y_t is autocorrelated(has short memory) then the limiting distribution of $Q_T / \sqrt{T}$ is V scaled by the square root of the long run variance of y_t. To allow for short range dependence in y_t,Lo(1991) modified the R/S statistic as follow:

$$\tilde{Q}_T = \frac{1}{\hat{\sigma}_T(q)}\left[\max_{1\le k\le T}\sum_{j=1}^{k}(y_j - \bar{y}) - \min_{1\le k\le T}\sum_{j=1}^{k}(y_j - \bar{y})\right] \quad (2.15)$$

Where the sample standard deviation is replaced by the square root of the Newey-West estimate of the long run variance with bandwidth q^2. Lo(1991) showed that if there is short memory but no long memory in y_t, $\tilde{Q}_T$ also converges to V, the range of a Brownian bridge.

GPH Test

Based on the fractionally integated process representation of a long memory time series as in (2.4), (Geweke, 1983) proposed a semi-nonparametric approach to testing for long memory. In particular, the spectral density of the fractionally integrated process y_t is given by:

$$f(\omega) = \left[4\sin^2\left(\frac{\omega}{2}\right)\right]^{-d} f_u(\omega) \quad (2.16)$$

where ω is the Fourier frequency, and $f_u(\omega)$ is the spectral density corresponding to u_t. Note that the fractional difference parameter d can be estimated by the following regression:

$$\ln f(\omega_j) = \beta - d\ln[4\sin^2(\frac{\omega_j}{2})] + e_j \quad (2.17)$$

for $j = 1,2,..., n_f(T)$. Geweke and Porter – Hudak (Geweke, 1983) showed that using a *periodogram* estimate of $f(\omega_j)$, the least square estimate $\hat{d}$ using the above regression is normally integrated in large samples if $n_f(T) = T^{\alpha}$ with $0 < \alpha < 1$

$$\hat{d} \sim N(d, \frac{\pi^2}{6\sum_{j=1}^{n_f}(U_j - \bar{U})^2})$$

where

$$U_j = \ln[4\sin^2(\frac{\omega_j}{2})]$$

and $\bar{U}$ is the sample mean of U_j, $j = 1,...,n_f$. Under the null hypothesis of no long memory $(d = 0)$, the t-statistic

$$t_{d=0} = \hat{d}.(\frac{\pi^2}{6\sum_{j=1}^{n_f}(U_j - \bar{U})^2})^{-1/2} \quad (2.18)$$

It has a limiting standard normal distribution.

Model overview of Long Memory Time Series

The raw daily data, Thai and Asia stock index, N225 (Nikkei Stock Average 225) Tokyo Stock Exchange, KLSE (KLSE Composite Index), Malaysian stock market, TWSE (Taiwan's composite index) Taiwan Stock Exchange, SETI (SET

Composite Index) the Stock Exchange of Thailand, SSEC (Shanghai Composite Index) Shanghai Stock Exchange, The BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange, JKSE (Jakarta Composite) Indonesia Jakarta Composite, PSI (PSE Composite Index) Philippine Stock Exchange, KS11 (KOSPI Index) Korean Stock Exchange are collected from Reuters for the period November 10, 1998 to November 10, 2008.

A stationary process y_t is the set of log daily price Asia Indexes. Based on the scalling property in (2.1) and the frequency domain property in (2.2) showed that a long memory process y_t can also be modeled parametrically by extending an integrated process to a fractionally integrated process. The fractional integration in a time series y_t as follow:

$$(1-B)^d (y_t - \mu) = u_t$$

where B denotes the lag operater , d is the fractional integration or fractional difference parameter , μ_t is a stationary short-memory disturbance with zero mean

SEMIFAR models are define by (Beran J. A., 1999) such that

$$\varphi(B)(1-B)^{\delta}\{(1-B)^m Y_i - g(t_i)\} = \epsilon_i \quad (3.1)$$

The SEMIFAR model extended by δ, m which -1/2< δ<1/2 for any d > -1/2. The number of times is m that y_t must be differenced to achieve stationary (Beran j. , 1995). The difference parameter is given by d = δ+m. The restriction of m is either 0 or 1 , when m=0, μ is the expectation of y_t; in contrast, when m=1, μ is the slop of the linear trend component in y_t

To allow for a possible deterministic trend in a time series, in addition to a stochastic trend, long memory and short memory component. The SEMIFAR model is based on the following extension to the FARIMA (p,d,0) model. The constant term μ is replaced by g(i_t), a smooth trend function on [0.1], with i=t/T. Using BIC choose autoregressive order p which is proposed by (Beran J. A., 1999)

3. Data and Estimation

3.1 Data

The descriptive statistics for log Asia prices Index are presented in Table 1. It shows that the mean of log Asia prices Index are between 6.23 and 9.48. The maximum mean is log index of N225 (Nikkei Stock Average 225) Tokyo Stock Exchange. The minimum mean is SETI (SET Composite Index) the Stock Exchange of Thailand. The JKSE (Jakarta Composite) Indonesia Jakarta Composite has the highest standard error at 0.63. The TWSE (Taiwan's composite index) Taiwan Stock Exchange has the lowest standard error, 0.22. The measuring of asymmetry of the distribution of the series around its mean is computed as skewness. The Positive skewness means that the distribution has a long right tail which SSEC (Shanghai Composite Index) Shanghai Stock Exchange, The BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange, JKSE (Jakarta Composite) Indonesia Jakarta Composite, KS11 (KOSPI Index) Korean Stock Exchange ,PSI (PSE Composite Index) Philippine Stock Exchange, KLSE (KLSE Composite Index), Malaysian stock market are all in the region of 0.22 to 1.28 and negative skewness implies that the distribution has a long left tail which N225 (Nikkei Stock Average 225) Tokyo Stock Exchange ,TWSE (Taiwan's composite index) Taiwan Stock Exchange, SETI (SET Composite Index) the Stock Exchange of Thailand are all in the region of -0.22 to -0.11. The reported Probability is the probability that a Jarque-Bera statistic do not exceeds (in absolute value) the observed value under the null hypothesis—a small probability value leads to the rejection of the null hypothesis of a normal distribution. For the all series displayed above, we reject the hypothesis of normal distribution at the 5% level and at the 1% significance level.

Table 1: Descriptive Statistics for Asian Stock Index

	China	India	Indonesia	Japan	Malaysia	Philippines	Korea	Thailand	Taiwan
Mean	7.4902	8.7109	6.6867	9.4845	6.8278	6.7380	7.5117	8.7628	6.2347
Median	7.3863	8.5357	6.5119	9.4974	6.7601	6.7277	7.5242	8.7420	6.3537
Maximum	8.7147	9.9462	7.9481	9.9443	7.6328	7.3240	8.2619	9.2304	6.8190
Minimum	6.9192	7.8633	5.8215	8.8767	5.9932	6.1276	6.8869	8.1450	5.5239
Std. Dev.	0.3993	0.5854	0.6287	0.2374	0.3876	0.2474	0.3528	0.2209	0.3643
Skewness	1.2822	0.5356	0.4945	-0.2163	0.3166	0.3459	0.2260	-0.1071	-0.2190
Kurtosis	4.0569	1.9136	1.8994	2.0271	2.0506	2.6304	2.1851	2.4477	1.5211
Jarque-Bera	836.6233	253.1160	238.1213	123.2874	141.6403	66.9115	94.4357	38.1648	258.7091
Probability	0	0	0	0	0	0	0	0	0
Observations	2610	2610	2610	2610	2610	2610	2610	2610	2610

Figure 1: Diagnostic Test Asian Stock Index from Autocorrelation Function.

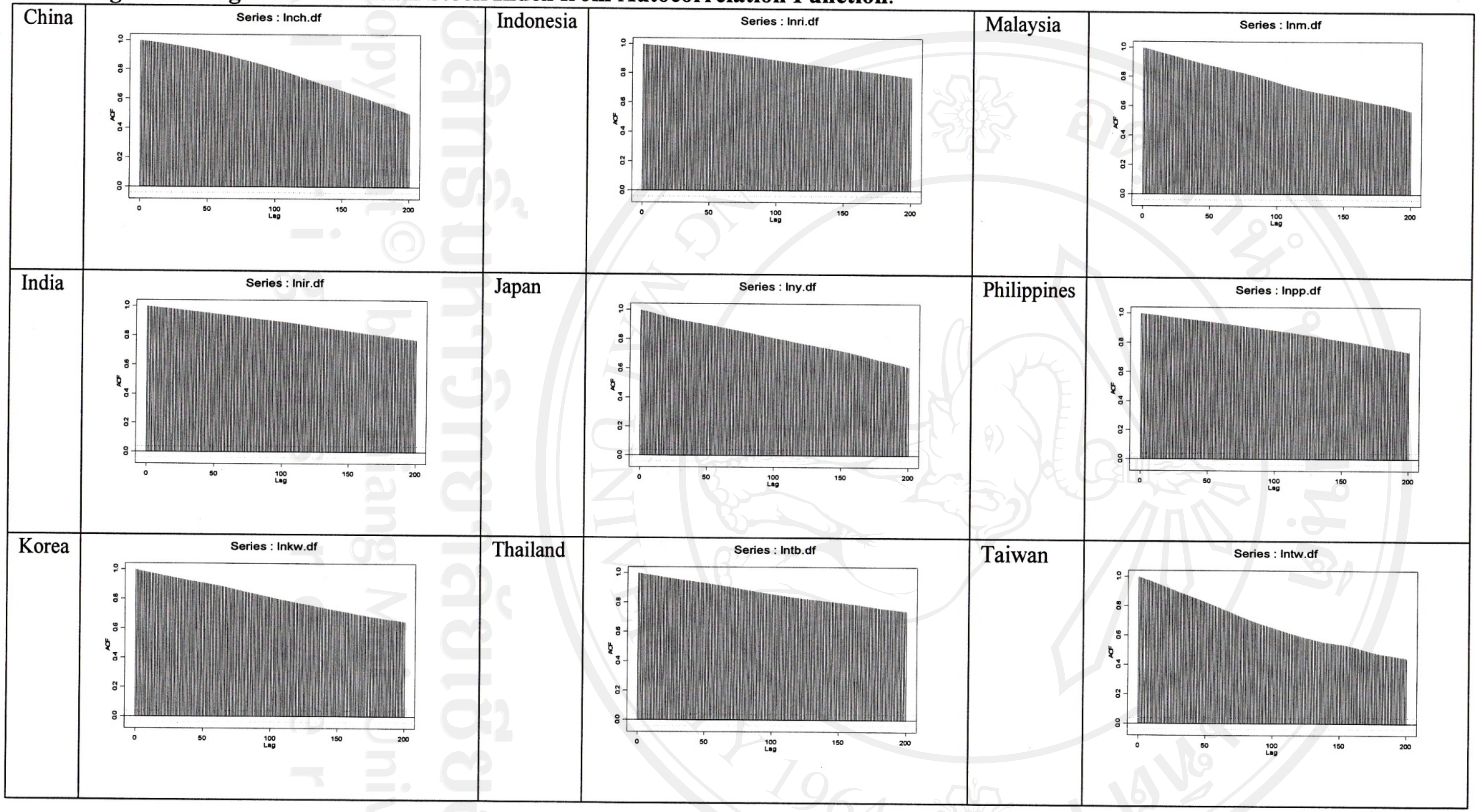


Figure 1 presents the autocorrelation of log daily Asia prices Index. The results show that the all indexes have long memory property in financial time series, consider the log daily Asia prices Index from November 10, 1998 to November 10, 2008. The autocorrelation of log daily Asia prices Index is highly persistent and remains very significant at lag 200. of the data will be tested by using Augmented Dickey-Fuller (ADF) test. The test is given as follows:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \varepsilon_t \quad (17)$$

The null hypothesis is θ = 0, if the null hypothesis is rejected, it means that the series y_t is stationary. The estimated values of θ and t-statistic of all returns are significant less than zero at 1% level that shows in table 2.

4. Empirical Results

Testing for Long Memory

In this section, the R/S statistic and GPH test are introduced for testing long memory property. They are not necessary for the autocorrelation to remain significant at large lags. The R/S statistic is the range of partial sums of deviations of a time series from its means, rescaled range, or range over standard deviation, or simply R/S statistic(Hurst, 1951). To allow for short range dependence in y_t, the R/S statistic was modified(LO, 1991). The GPH test is the fractionally integrated process representation of a long memory time series, and the semi-nonparametric approach to testing for long memory. Under the null hypothesis of no long memory $(d = 0)$, has a limiting standard normal distribution. The result shows in the Table 2. The testing shows that all log daily Asia prices Index are significant at 1% level of significance. It confirms the long memory property of log daily Asia prices Index.

Table 2: Testing Long Model for Asian Stock Index

	modified R/S test	GPH test	
		d-value	statistic
China	5.3791**	1.2079	11.8578**
India	6.9926**	1.2178	11.9559**
Indonesia	7.1044**	1.3246	13.0035**
Japan	6.6181**	0.9292	9.1218**
Malaysia	6.1245**	1.1247	11.0416**
Philippines	6.7572**	1.0539	10.3464**
Korea	6.7156**	1.0073	9.8892**
Thailand	7.4858**	1.0219	10.0321**
Taiwan	6.2565**	0.9661	9.4843**

Null Hypothesis: no long-term dependence
 * : significant at 5% level
** : significant at 1% level

Estimation of Long memory with SEMIFAR model

The FARIMA model was extended by δ, m which -1/2< δ<1/2 for any d > -1/2. The difference parameter is given by d = δ+m. The restriction of m is either 0 or 1 , when m=0, μ is the expectation of y_t; in contrast, when m=1, μ is the slop of the linear trend component in set of data. in addition to a stochastic trend, long memory and short memory component. The SEMIFAR replaced constant term μ by $g(i_t)$, a smooth trend function on [0.1], with i=t/T. Using BIC choose autoregressive order p which is proposed by (Beran J. A., 1999)

The Table 3 shows estimation from SEMIFAR model. The BIC show the value which is parsimonious model. The BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange, N225 (Nikkei Stock Average 225) Tokyo Stock Exchange, PSI (PSE Composite Index) Philippine Stock Exchange show the value of d which equal -0.0489, -0.0164, -0.0164. They are in rank -1/2<d<0 which have stationary and short memory. The SSEC (Shanghai Composite Index) Shanghai Stock Exchange, JKSE (Jakarta

Composite) Indonesia Jakarta Composite , KLSE (KLSE Composite Index) Malaysian stock market, KS11 (KOSPI Index) Korean Stock Exchange, SETI (SET Composite Index) the Stock Exchange of Thailand, TWSE (Taiwan's composite index) are stationary and long memory which the d value equal 0.1148, 0.0747, 0.0845, 0.0098, 0.0127, 0.0377. They are in rank $0<d<1/2$ which have stationary and long memory. The estimated m value of all Indexes is equal zero, except BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange which m value equal 1. The BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange has slop of the linear trend because of m value equal one.

The Figure 2 shows the diagnostic test. Which indicates the original time series, the estimated smooth trend component, the fitted values and model residuals, the smooth trend component is also plotted with a confidence band. If the trend falls outside the confidence band, it indicates that the trend component is significant. In the all case, the trend of log price indexes of JKSE (Jakarta Composite), Indonesia Jakarta Composite, Malaysian stock market, KS11 (KOSPI Index), Korean Stock Exchange, SETI (SET Composite Index), the Stock Exchange of Thailand appear to be very significant, at least for the time period investigated. However, the log price indexes of SSEC (Shanghai Composite Index) Shanghai Stock Exchange, BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange, N225 (Nikkei Stock Average 225) Tokyo Stock Exchange, PSI (PSE Composite Index) Philippine Stock Exchange and TWSE (Taiwan's composite index) Taiwan Stock Exchange fall inside the confidence band. The trend component is not significant. The ACF plot of all log price Asia Indexes present that the long memory behavior have been well capture by the model.

Prediction

To illustrate prediction from long memory process, the lag polynomial can be expressed as a finite order polynomial so that a FARIMA (p,d,q) model can be equivalently expressed as an AR(∞) model. The best linear prediction coefficient can also be visualized to see the effects of using more lags for prediction. In this paper, generating coefficient plot show in Figure 3 which also, presents the forecast log price Asia Indexes. Table 4 shows the value which estimated from SEMIFAR models. The graph contains the predicted values, standard errors of predictions and generating coefficient plot of the coefficient are not change the prediction.

5. Conclusion

The traditional stationary ARMA processes often cannot capture the high degree of persistence in financial time series, the class of non-stationary unit root. The long memory process can provide a good description of many highly persistent financial time series. The log daily Asia prices Index from November 10, 1998 to November 10, 2008 have highly persistent and remains very significant at lag 200 which presents in the autocorrelation function. The R/S statistic and GPH test which are not necessary for the autocorrelation to remain significant at large lags are introduced for testing long memory property. At 1% level of significance, they confirm the long memory property of log daily Asia prices Index. Estimation of Long memory was introduced by FARIMA model which extended by δ, m which $-1/2< \delta<1/2$ for any $d > -1/2$. The difference parameter is given by $d = \delta+m$. The restriction of m is either 0 or 1 , when m=0, μ is the expectation of y_t; in contrast, when m=1, μ is the slop of the linear trend component in y_t. In addition to a stochastic trend, long memory and short memory component.

Table 3a: The Asian Stock Index in SEMIFAR model

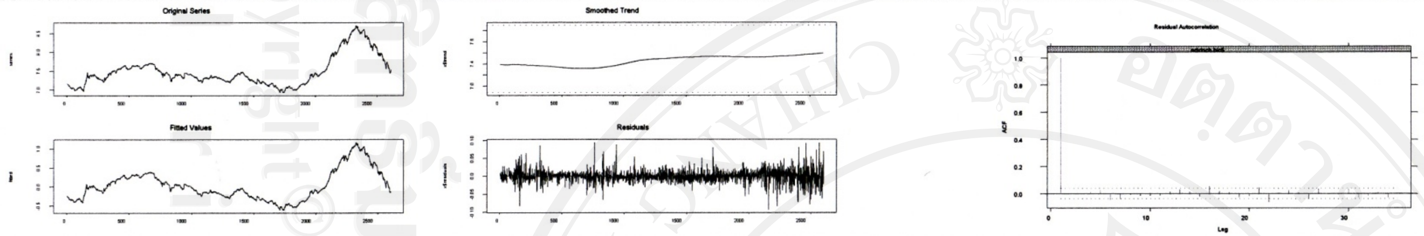
	China		India		Indonesia		Japan		Malaysia	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
d	0.114	0.030**	-0.048	0.027	0.074	0.017**	-0.016	0.015	0.084	0.066
AR(1)	0.880	0.035**	0.104	0.034**	0.991	0.003**	0.999	0.001**	1.052	0.068**
AR(2)	0.025	0.028	-	-	-	-	-	-	-0.085	0.045
AR(3)	0.091	0.025**	-	-	-	-	-	-	0.068	0.029*
AR(4)	-	-	-	-	-	-	-	-	-0.084	0.0294**
AR(5)	-	-	-	-	-	-	-	-	0.039	0.022
differenced (m)	0		1		0		0		0	
Information Criteria:										
log-likelihood	7035.393		6936.484		7136.788		7207.116		8175.483	
BIC	-14039.3		-13857.2		-14257.8		-14398.5		-16303.8	

Table 3b: The Asian Stock Index in SEMIFAR model

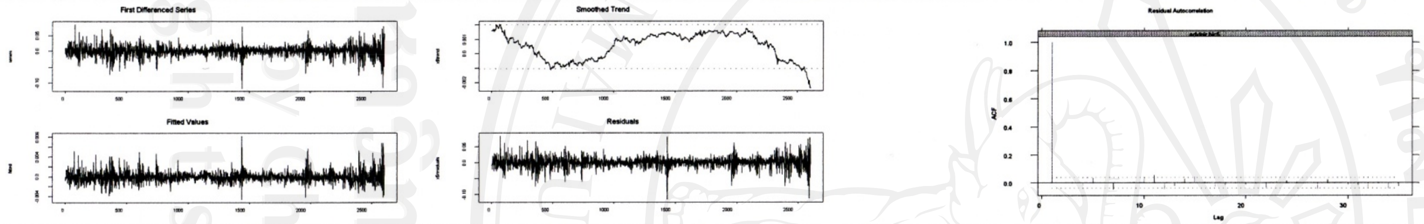
	Philippines		Korea		Thailand		Taiwan	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
d	-0.069	0.029*	0.009	0.017	0.012	0.048	0.037	0.0168*
AR(1)	0.194	0.036**	0.991	0.002**	1.020	0.053**	0.995	0.0022**
AR(2)	-	-	-	-	0.059	0.037	-	-
AR(3)	-	-	-	-	-0.086	0.029**	-	-
AR(4)	-	-	-	-	-	-	-	-
AR(5)	-	-	-	-	-	-	-	-
differenced (m)	0		0		0		0	
Information Criteria:								
log-likelihood	7399.473		6596.669		7130.691		7072.041	
BIC	-14783.2		-13177.6		-14229.9		-14128.4	

Figure 2: Diagnostic Test Asian Stock Index from SEMIFAR Model, Original Plot, Fitted Plot, Smoothed Trend Plot, Residuals Plot, Residuals Autocorrelation

China



India



Indonesia

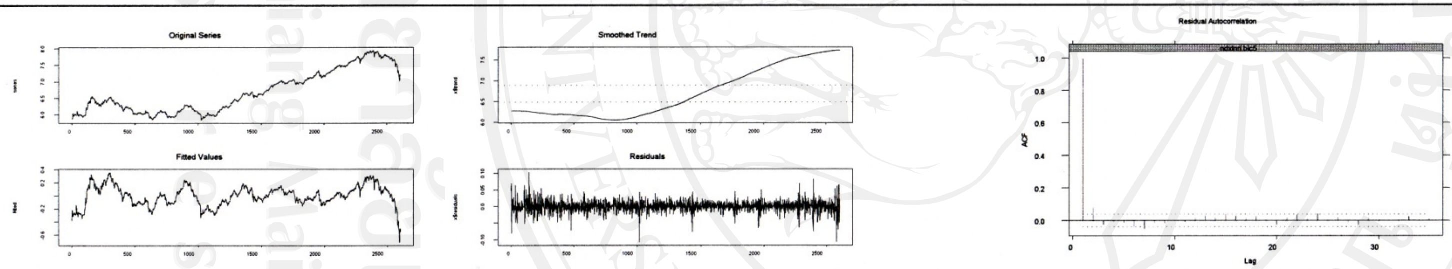


Figure 2: Diagnostic Test Asian Stock Index from SEMIFAR Model, Original Plot, Fitted Plot, Smoothed Trend Plot, Residuals Plot, Residuals Autocorrelation (Continued)

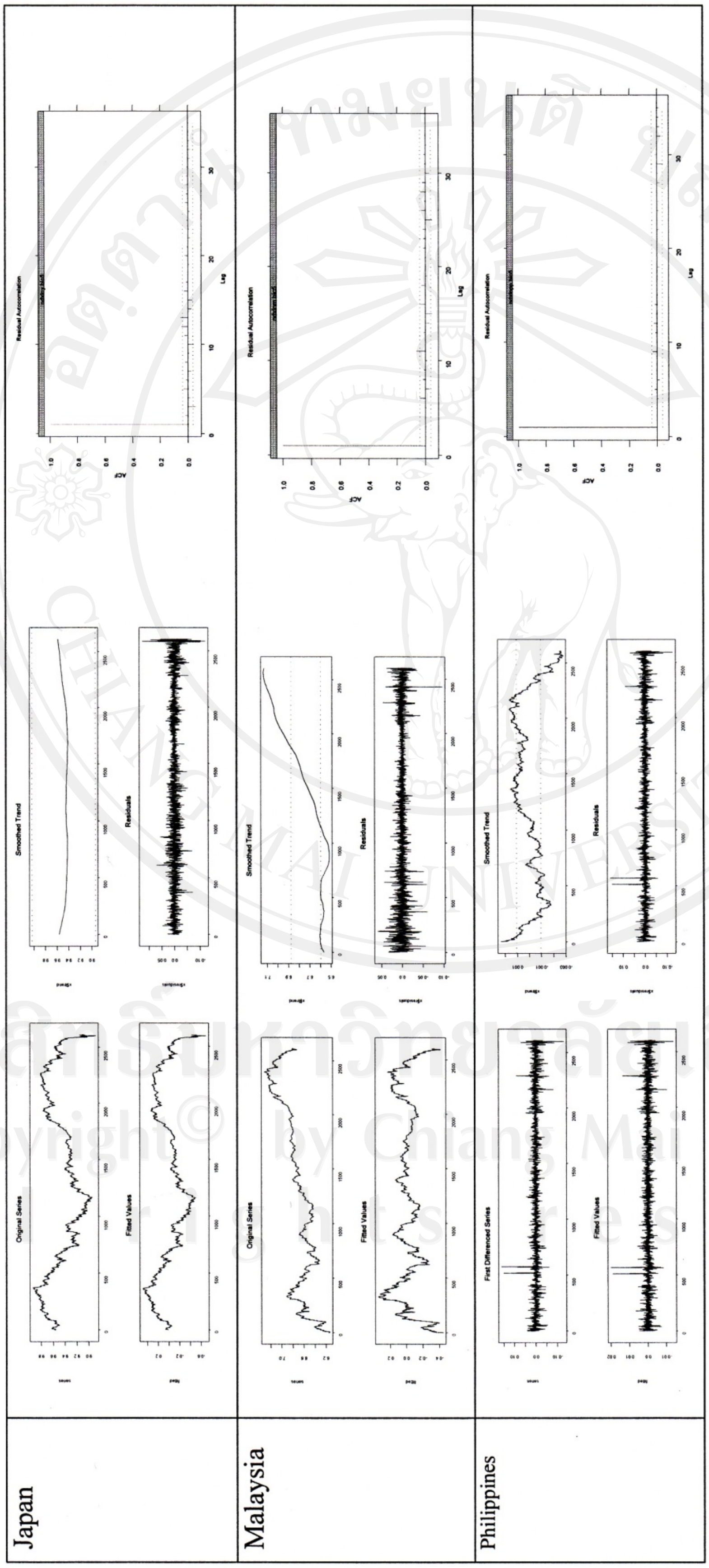


Figure 2: Diagnostic Test Asian Stock Index from SEMIFAR Model, Original Plot, Fitted Plot, Smoothed Trend Plot, Residuals Plot, Residuals Autocorrelation (Continued)

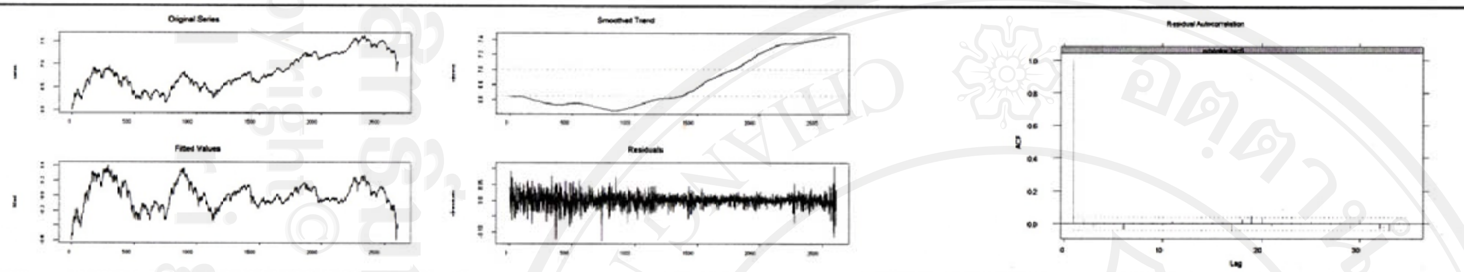
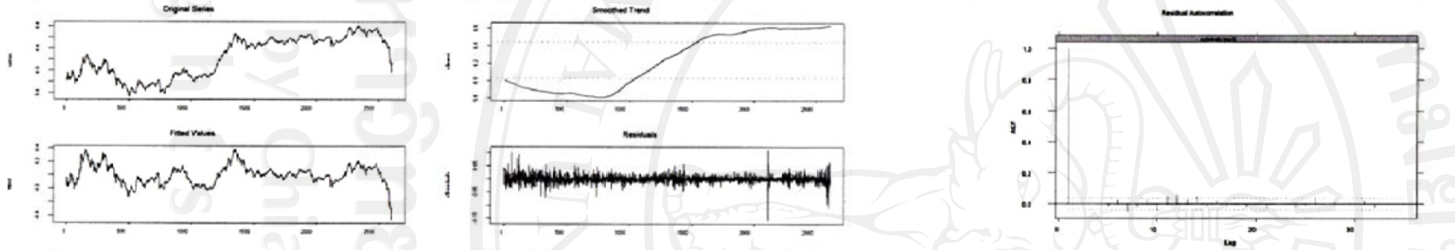
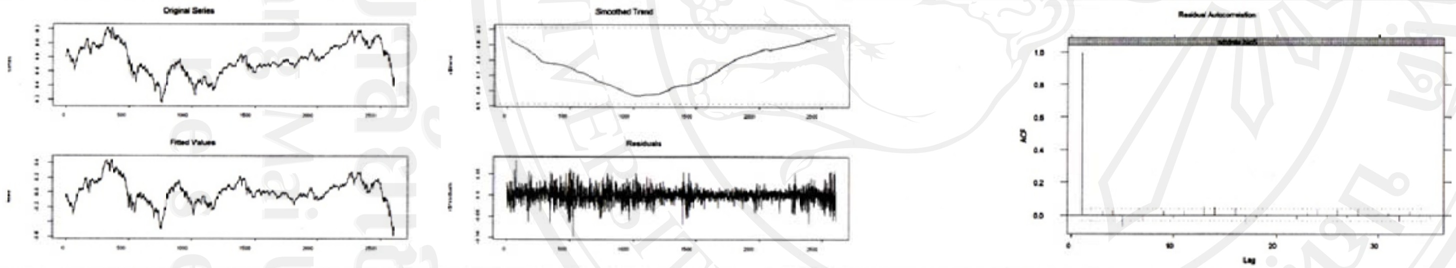
Korea	
Thailand	
Taiwan	

Figure 3: Plotted Asian Stock Index from SEMIFAR Model

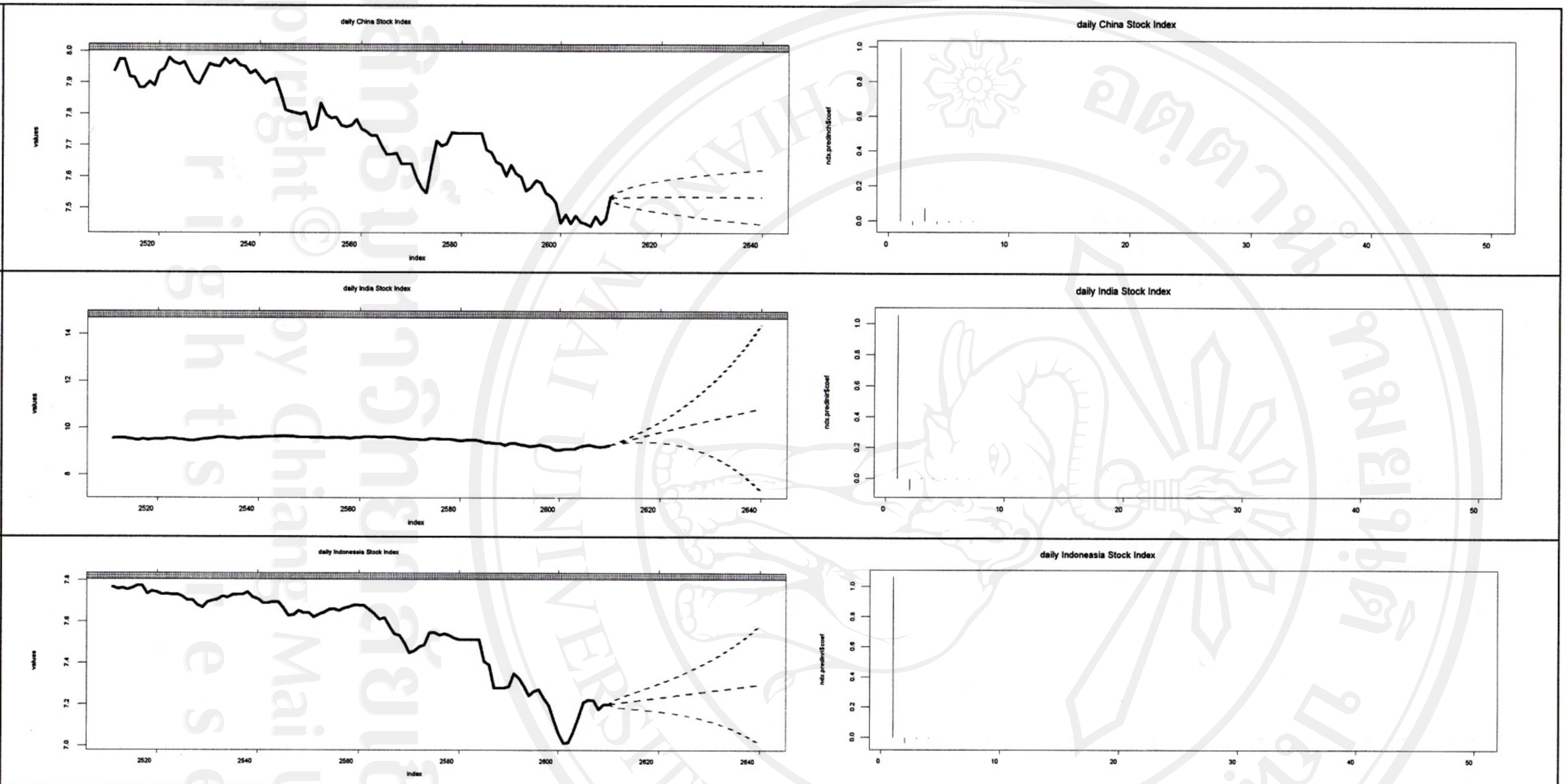


Figure 3: Plotted Asian Stock Index from SEMIFAR Model (Continued)

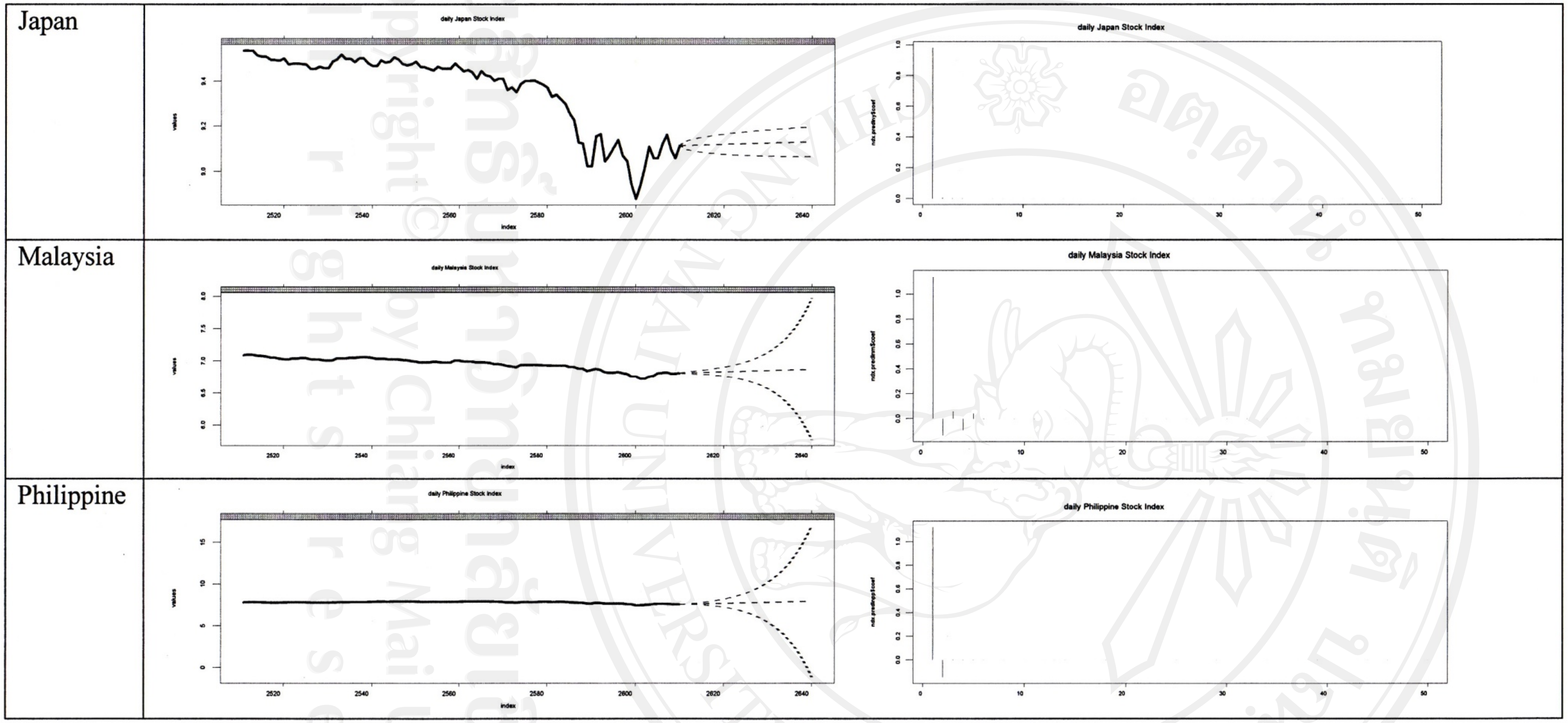


Figure 3: Plotted Asian Stock Index from SEMIFAR Model (Continued)

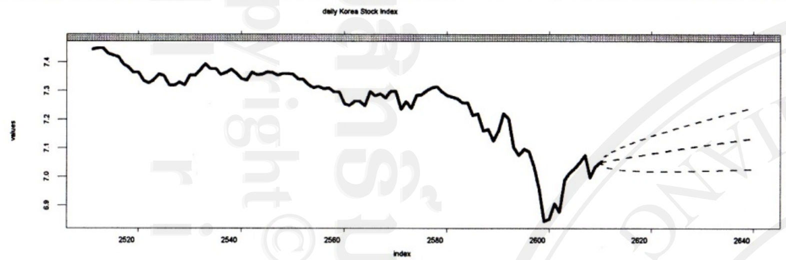
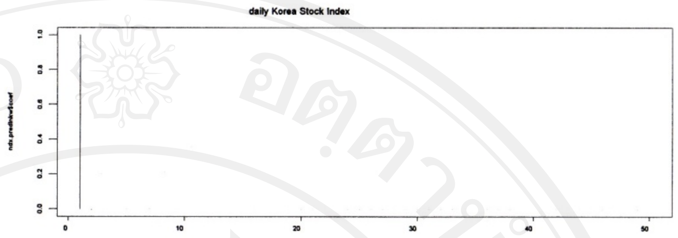
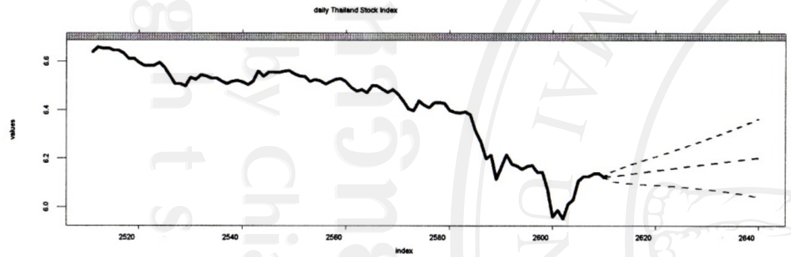
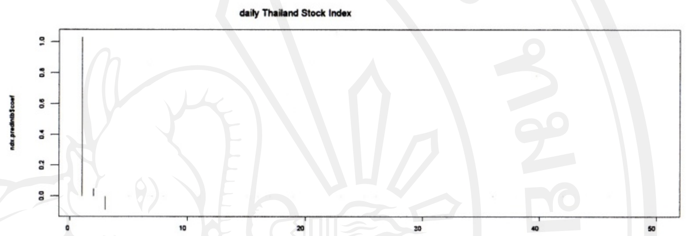
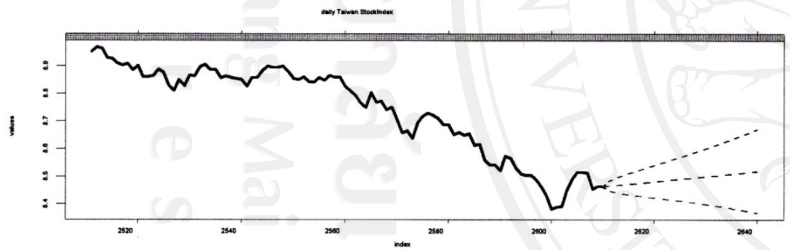
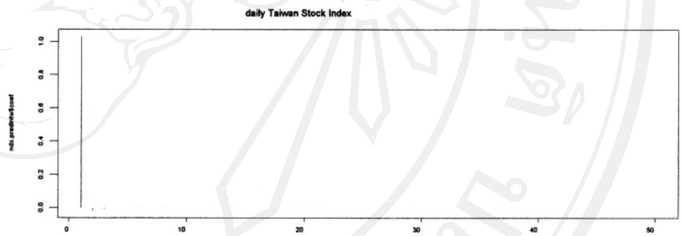
Korea		
Thailand		
Taiwan		

Table 4: The Prediction Value from SEMIFAR Model (next 30 periods)

China	India	Indonesia	Japan	Malaysia	Philippines	Korea	Thailand	Taiwan
1869.64	11179.09	1344.93	9082.46	905.96	1966.87	1156.21	457.42	4747.15
1864.41	11847.83	1349.24	9086.09	908.41	1995.20	1159.80	457.97	4754.75
1869.08	12544.03	1353.57	9090.63	911.05	2022.93	1163.40	459.21	4762.37
1871.32	13271.84	1357.91	9096.09	912.60	2050.42	1167.01	460.49	4770.47
1872.26	14033.46	1362.26	9101.55	914.61	2077.67	1170.52	461.79	4779.06
1873.19	14829.89	1366.63	9106.10	916.53	2104.64	1174.03	463.13	4787.67
1873.76	15666.81	1371.01	9111.57	918.37	2131.54	1177.56	464.43	4796.30
1874.13	16542.70	1375.40	9117.04	920.30	2158.35	1180.98	465.77	4804.94
1874.51	17460.56	1379.81	9122.51	922.23	2185.06	1184.53	467.08	4814.08
1874.88	18423.83	1384.23	9127.98	924.17	2211.66	1187.97	468.39	4822.75
1875.07	19434.40	1388.67	9132.55	926.02	2238.14	1191.42	469.75	4831.92
1875.44	20494.26	1393.12	9138.03	927.97	2264.71	1194.76	471.07	4841.11
1875.82	21605.43	1397.58	9143.51	929.92	2291.13	1198.23	472.34	4850.32
1875.82	22774.57	1402.06	9148.09	931.78	2317.63	1201.59	473.66	4859.54
1875.63	23999.78	1406.56	9153.58	933.65	2344.44	1204.96	474.99	4868.79
1875.44	25285.84	1411.07	9159.07	935.61	2371.08	1208.34	476.28	4878.05
1875.26	26635.49	1415.59	9164.57	937.48	2397.78	1211.60	477.61	4887.32
1874.88	28051.57	1419.98	9169.15	939.36	2424.55	1215.00	478.90	4896.62
1874.51	29537.03	1424.53	9174.65	941.24	2451.36	1218.29	480.20	4905.93
1874.32	31094.93	1428.96	9180.16	943.13	2478.48	1221.58	481.50	4915.26
1873.94	32728.45	1433.54	9184.75	945.01	2505.39	1224.88	482.80	4924.61
1873.57	34444.34	1437.99	9189.35	946.81	2532.60	1228.07	484.06	4933.97
1873.19	36242.94	1442.45	9194.86	948.71	2559.58	1231.39	485.36	4943.36
1872.82	38127.84	1446.93	9199.46	950.61	2586.60	1234.60	486.63	4952.76
1872.63	40102.74	1451.42	9204.06	952.41	2613.90	1237.81	487.89	4962.18
1872.26	42175.72	1455.93	9209.58	954.23	2640.70	1240.91	489.21	4971.61
1872.26	44346.98	1460.45	9213.27	956.14	2667.77	1244.14	490.49	4981.57
1872.07	46620.70	1464.98	9217.88	957.95	2694.59	1247.25	491.76	4991.04
1872.07	49006.10	1469.53	9222.49	959.78	2721.40	1250.38	493.00	5000.53
1871.88	51508.39	1473.95	9227.10	961.60	2747.92	1253.51	494.28	5010.04

The SEMIFAR model extend constant term μ which is replaced by $g(i_t)$, a smooth trend function on [0.1], with i=t/T. Using BIC choose autoregressive order p which is proposed by (Beran J. A., 1999) .

The BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange, N225 (Nikkei Stock Average 225) Tokyo Stock Exchange, PSI (PSE Composite Index) Philippine Stock Exchange have d value in rank $-1/2<d<0$ which are stationary and short memory. The SSEC (Shanghai Composite Index) Shanghai Stock Exchange, JKSE (Jakarta Composite) Indonesia Jakarta Composite, KLSE (KLSE Composite Index) Malaysian stock market, SETI (SET Composite Index) the Stock Exchange of Thailand, KS11 (KOSPI Index) Korean Stock Exchange, TWSE (Taiwan's composite index) Taiwan stock Exchange are stationary and long memory, because the d value are in rank $0<d<1/2$. The m value of BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange equals 1 that it has slop of the linear trend. The diagnostic test indicates the log price indexes of JKSE (Jakarta Composite) Indonesia Jakarta Composite, KLSE (KLSE Composite Index) Malaysian stock market, KS11 (KOSPI Index) Korean Stock Exchange, SETI (SET Composite Index) the Stock Exchange of Thailand appear to be very significant, at least for the time period investigated. However, the log price indexes of SSEC (Shanghai Composite Index) Shanghai Stock Exchange, BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange, N225 (Nikkei Stock Average 225), Tokyo Stock Exchange, PSI (PSE Composite Index) Philippine Stock Exchange and TWSE (Taiwan's composite index) Taiwan Stock Exchange fall inside the confidence band. The ACF plot of all log price Asia Indexes present that the long memory behavior have been well capture by the model. The graph contains the predicted values, standard errors of predictions and generating coefficient plot of the coefficient are not change the prediction.

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Analysis and Comparison of Asian Stock Markets Using Integrated Time-Varying Model Processing

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Abstract

This paper analyses the risk-return relationships of Asian stock markets with a time-varying CAPM model for ten Asian Stock Markets. We purpose the Adaptive Least Squares with Kalman foundations, Bayesian, and Quantile regression for estimating the time-varying CAPM model and comparing the alpha, beta for each estimator. The values of time-varying alpha and beta, estimated from Quantile regression, are much greater and lesser than the estimating- value of the time- varying alpha and beta, estimated from The Bayesian and Kalman filtered estimator at quantile 2.5% and 97.5%. The Bayesian and Kalman filtered estimator present the closely value.

Keywords: *Time-varying CAPM, State-Space model, Kalman filtered, Bayesian, Quantile regression.*

1. Introduction

Many countries in Asia experienced steep falls in their exchange rates in late 1997 and early 1998. The collapse of the Thai baht's peg in July 1997 is recorded as the beginning of the rapid spread of the financial crisis in East Asia. There are the evidence to support the existence of relationship between the stock markets of Thailand and Indonesia, and between Thailand and the Philippines, over both the pre- and post-1997 crisis periods (Daly, 2003). The Singapore and Taiwan are cointegrating with Japan while Hong Kong is cointegrating with the United States and the United Kingdom. There are no long run equilibrium relationship between Malaysia, Thailand and Korea and the developed markets of the United States, the United Kingdom and Japan. The relationship between the developed and emerging markets also change over time .The relationship between the developed and emerging markets also change over time (Wong, Penm ,Terrell, Lim, 2004).

One important evaluation for the relationship is to check the CAPM, the risk-return relationships with a time-varying CAPM model. The CAPM states that the systematic difference in security returns can be explained by a single measure of risk. The CAPM are often debatable due to many obstacles, including non-stationarity of beta coefficient and risk premium, inadequate proxy of the market portfolio, straightforward relationship between expected return on an asset and market risk premium, and joint hypothesis test problems associated with unobservable expected returns.

In previous empirical test, the model is biased against finding a significant relationship between beta and expected returns because the relationship between beta and realized returns is conditional on the market return. In bull markets, high beta securities should be rewarded for bearing risk with higher returns than low beta securities, but in bear markets high-risk, high-beta securities experience lower returns than low beta securities. Pettengill, Sundaram, and Mathur (1995) confirm a significant direct relationship between beta and returns in up markets and a significant inverse relationship between beta and returns in down markets. The suggestions in many empirical researches show that the testing methodology is inappropriate (Calvet and Lefoll, 1989; Roll and Ross, 1994; Chan and Chen, 1988; Fama and French, 1992).

In particular, most of the CAPM tests hold beta coefficients constant in the sense of developing to explain differences in risks across capital assets. (Jagannathan and McGrattan, 1995). However, the firms often change their risk structures in conjunction with the macroeconomic environment that is the firm will vary over time. Hence, the examining the relationship between return and beta using time series tests in the sense of time-varying properties of beta coefficients seems more realistic than the non-stochastic beta assumption.

Although Jagannathan and Wang (1994) point out that the constant beta assumption is not reasonable. (C.f Ferson and Harvey, 1991; Fama and French, 1992; Chan and Chen, 1988; Groenwold and Fraser, 1999; Black and Fraser, 2000; Fraser et al., 2000). Jagannathan and Wang (1995) and Lettau and Ludvigson (2001) show that conditional CAPM with a time-varying beta outperforms the unconditional CAPM with a constant beta.

The purpose of this paper examines the asymmetric risk-return relationships in the up and down markets with a time-varying beta model. The Adaptive Least Squares with Kalman foundations proposed by McCulloch (2006), Bayesian (Quintana, Iglesias and Galea (2005); Johnson and Sakoulis (2008); Busse and Irvine (2006);

Christodoulakis (2002); Herold and Maurer (2003)), Quantile regression (Ma and Pohlman(2008)) , are used to estimate the time-varying beta model.

2. Financial and Econometric Model Base with Time Varying

In this section, we are going to give a brief summary about the time varying models, such us State Space CAMP, Bayesian CAMP and Quantile regression CAMP that economists often used. State Space modeling in macroeconomics and finance has become widespread over the last decade. Many dynamic time series models in economics and finance may be represented in State Space form, as the system of equation. The work of (Zellner and Chetty 1965) shows the optimal Bayesian portfolio problem by Bayes' rule, the posterior density $p(r|\theta)$ is proportional to the product of the sampling density (the likelihood function) and the prior density, $f(r|\theta)p(\theta)$. The Koenker and Bassett (1978) developed the median (quantile) regression estimator to minimize the symmetrically weighted sum of absolute errors (where the weight is equal to 0.5) to estimate the conditional median (quantile) function. Then we will present an integrated procedure to construct an appropriate model for the stock data.

2.1 State Space CAPM

Typically, the State Space models can be found in most books (Durbin & Koopman (2001), and Chan (2002)). The State Space model equation can be compactly expressed as

$$\begin{pmatrix} \alpha_{t+1} \\ y_t \end{pmatrix} = \underset{(m\times N)\times 1}{\delta_t} + \underset{(m+N)\times m}{\Phi_t} \,.\underset{m\times 1}{\alpha_t} + \underset{(m\times N)\times 1}{\mu_t} \tag{2.1}$$

where $\alpha_t \sim$ N(**a**, **P**), $\mu_t \sim$ WN (0,1)

and $\delta_t \begin{pmatrix} d_t \\ c_t \end{pmatrix}, \Phi_t = \begin{pmatrix} T_t \\ Z_t \end{pmatrix}, \mu_t = \begin{pmatrix} H_t \mu_t \\ G_t \varepsilon_t \end{pmatrix}, \Omega_t = \begin{pmatrix} H_t H_t' & 0 \\ 0 & G_t G_t' \end{pmatrix}$.

The initial value parameters are summarized in the (m + 1) × m matrix $\Sigma = \begin{pmatrix} P \\ a' \end{pmatrix}$. The smoothed estimate of the response y_t and its variance are computed using

$$\hat{y}_t = c_t + Z_t \hat{\alpha}_t \qquad \mathrm{var}(\alpha_t | Y_n) = Z_t \ \mathrm{var}(\alpha_t | Y_n) Z_t' \tag{2.2}$$

The smoothed disturbance estimates are the estimates of the measurement equations innovations ε_t and transition equation innovations η_t based on all available information Y_n, and are denoted $\hat{\varepsilon}_t = E[\alpha_t|Y_n]\left(\text{or } \varepsilon_{t|n}\right)$ and $\hat{\eta}_t = E[\eta_t|Y_n]\left(\text{or } \eta_{t|n}\right)$, respectively. The computation of $\hat{\varepsilon}_t$ and $\hat{\eta}_t$ from the Kalman smoother algorithm is described in Durbin & Koopman (2001). These smoothed disturbance estimates can be useful for parameter estimation by maximum likelihood and for diagnostic checking. The vector of prediction errors v_t and prediction error variance matrices F_t are computed from the Kalman filtered recursions.

State Space representation of a time varying parameter regression model consider a Capital Asset Pricing Model (CAPM) with time varying intercept and slope

$$\begin{aligned} y_t &= \alpha_t + \beta_{M,t} x_{M,t} + v_t, && v_t \sim \text{WN}, \\ \alpha_{t+1} &= \alpha_t + \xi_t, && \xi_t \sim \text{WN}, \\ \beta_{M,t+1} &= \beta_{M,t} + \varsigma_t && \varsigma_t \sim \text{WN}, \end{aligned} \tag{2.3}$$

where y_t denotes the return on an asset in excess of the risk free rate, and $x_{M,t}$ denotes the excess return on a market index. In this model, both the abnormal excess return α_t and asset risk $\beta_{M,t}$ are allowed to vary over time following a random walk specification. Let $\alpha_t = (\alpha_t, \beta_{M,t})'$, $x_t = (1_t, x_{M,t})'$, $H_t = diagccc(\sigma_{\xi_t}, \sigma_{\zeta})'$ and $G_t = \sigma_v$. Then the State Space form equation (2.1) of equation (2.3) is $\begin{pmatrix} \alpha_{t+1} \\ y_t \end{pmatrix} = \begin{pmatrix} I_2 \\ x_t' \end{pmatrix} \alpha_t + \begin{pmatrix} H_t \eta_t \\ G_t \varepsilon_t \end{pmatrix}$ and has parameters

$$\Phi_t = \begin{pmatrix} I_2 \\ x_t' \end{pmatrix}, \Omega = \begin{pmatrix} \sigma_\xi^2 & 0 & 0 \\ 0 & \sigma_\zeta^2 & 0 \\ 0 & 0 & \sigma_{v\xi}^2 \end{pmatrix} \tag{2.5}$$

The variance matrix P of the initial state vector α_1 is assumed to be of the form $p = p_* + \kappa p_\infty$. Since α_t is I(1) the initial state vector α_1 requires an infinite variance so it is customary to set a = 0 and P = $k\text{I}_2$ with $k \to \infty$. Using equation (2.5), the initial variance is specified with p_*= 0 and p_∞ = I_2. Therefore, the initial state matrix $\Sigma = \begin{pmatrix} P \\ a' \end{pmatrix}$ for the time varying CAPM has the form $\Sigma = \begin{pmatrix} -1 & 0 \\ 0 & -1 \\ 0 & 0 \end{pmatrix}$. The State Space parameter matrix Φ_t in equation (2.5) has a time varying system element Z_t= x_t'. The specification of the State Space form for the time varying CAPM requires values for the variances σ_ξ^2 σ_ζ^2 and σ_v^2 as well as a data matrix X whose rows correspond with $Z_t = x_t' = (1, r_{M,t})$. The values Φ_t associated with x_t' in the third row are set to zero. In the general State Space model equation (2.1), it is possible that all of the system matrices δ_t, Φ_t and Ω_t have time varying elements.

The typical CAPM regression model is, $y_t = \alpha + \beta_M x_{M,t} + \xi_t$, ξ_t~WN. The y_t denotes the return on an asset in excess of the risk free rate, and $x_{M,t}$ is the excess return on a market index. The State Space representation is given by $\begin{pmatrix} \alpha_{t+1} \\ y_t \end{pmatrix} = \begin{pmatrix} I_k \\ x_t' \end{pmatrix} \alpha_t + \begin{pmatrix} 0 \\ \sigma_\xi \xi_t \end{pmatrix}$ with $x_t = (1, x_{M,t})'$ and the state vector satisfies $\alpha_{t+1} = \alpha_t = \beta = (\alpha, \beta_M)'$. The State Space system matrices are $T_t = I_K$, $Z_t = x_t'$, $G_t = \sigma_\xi$ and $H_t = 0$. Estimating the CAPM with time varying coefficients in equation (2.3) subject to random walk evolution are showed in data. Neumann (2002) surveys several estimation strategies for time varying parameter models and concludes that the State Space model with random walk specifications for the evolution of the time varying parameters generally performs very well. The log-likelihood is parameterized using $\varphi = (\ln(\sigma_\xi^2), \ln(\sigma_\varsigma^2), \ln(\sigma_v^2))'$ so that $\sigma^2 = (\exp(\varphi_1), \exp(\varphi_2), \exp(\varphi_3))'$. The maximum likelihood estimates for φ which estimates of $\varphi = (\ln(\sigma_\xi^2), \ln(\sigma_\varsigma^2), \ln(\sigma_v^2))'$. These methods estimated the standard deviations σ_ξ σ_ς and σ_v as well as estimated standard errors.

2.2 Bayesian CAPM

The predictive density function reflects estimation risk explicitly since it integrates over the posterior distribution, which summarizes the uncertainty about the model parameters, updated with the information contained in the observed data. The Bayes' rule, the posterior density $p(r|\theta)$ is proportional to the product of the sampling density (the likelihood function) and the prior density, $f(r|\theta)\,p(\theta)$.

The decision-making under uncertainty are represented portfolio choice problem. Let r_{T+1} denote the vector $(N \times 1)$ of next-period returns and W current wealth. The next-period wealth is $W_{T+1} = W(1 + \omega' r_{T+1})$ in the absence of a risk-free asset. The next-period wealth $W_{T+1} = W(1 + r_f + \omega' r_{T+1})$ is a risk-free asset with return r_f is present. Let ω denote the vector of asset allocations. The optimal portfolio decision consists of choosing ω that maximizes the expected utility of next-period's wealth, $\max_\omega E(U(W_{T+1})) = \max_\omega \int U(W_{T+1})\, p(r|\theta)\, dr$, subject to feasibility constraints, where θ is the parameter vector of the return distribution and U is a utility function generally characterized by a quadratic or a negative exponential functional form. The distribution of returns is $p(r|\theta)$,. The $\max_{\omega} E(U(W_{T+1})) = \max_{\omega} \int U(W_{T+1})\, p(r|\theta)\, dr$, is conditional on the unknown parameter vector θ, which are set θ equal to its estimate $\hat{\theta}(r)$ based on some estimator of the data r (often the maximum likelihood estimator). Then, the optimal allocation given by $\omega^* = \arg\max_{\omega} E\left(U(\omega' r) \middle| \theta = \hat{\theta}(r)\right)$.

The return generating process for the stock's excess return is $r_i = \alpha + \beta' f_t + \varepsilon_t, t = 1,\ldots,T,$. The f_t is denoted a (K x 1) vector of factor returns (returns to benchmark portfolios), and ε_t is a mean-zero disturbance term. Then, the slopes of the regression in $r_i = \alpha + \beta' f_t + \varepsilon_t$ are stock's sensitivities (betas). In a single factor model such as the CAPM, the benchmark portfolio is the market portfolio. The implications for portfolio selection of varying prior beliefs about a pricing model are expressed, the prior mean of α , α_0, is set equal to zero. It could have a non-zero value. The prior variance σ_α of α reflects the investor's degree of confidence in the prior mean a zero value of σ_α represents dogmatic belief in the validity of the model; $\sigma_\alpha = \infty$ suggests complete lack of confidence in its pricing power.

2.3 Quantile Regression CAPM

The other conditional quantile functions are estimated by minimizing an asymmetrically weighted sum of absolute errors, where the weights are functions of the quantile of interest. Thus, Quantile regression is robust to the presence of outliers. Engle and Manganelli (1999) and Morillo (2000) used in financial applications. The general Quantile regression model, as described by Buchinsky (1998), is $y_i = x_i'\beta_\theta + \mu_{\theta i}$ or, alternatively, $\theta = \int_{-\infty}^{x_i'\beta_\theta} f_y(s|x_i)\, ds$, where β_θ is an unknown k × 1 vector of regression parameters associated with the θ_{th} percentile x_i is a k × 1 vector of independent variables, y_i is the dependent variable of interest, and $\mu_{\theta i}$ is an unknown error term. The θ_{th} conditional quantile of y given x is $Quant_\theta(\mu_{\theta i}|x_i) = x_i'\beta_\theta$.Its estimate is given by $x_i'\hat{\beta}_\theta$. As θ increases continuously, the conditional distribution of y given x is traced out. Although many of the empirical Quantile regression papers assume that the errors are independently and identically distributed (i.i.d.), the only necessary assumption concerning $\mu_{\theta i}$ is $Quant_\theta(\mu_{\theta i}|x_i) = 0$, That is, the conditional θ_{th} quantile of the error term is equal to zero. Thus, the Quantile regression method involves allowing the marginal effects to change for firms at different points in the conditional distribution by estimating β_θ using several different values of $\theta, \theta \in (0,1)$ It is in this way that Quantile regression allows for parameter heterogeneity across different types of assets. Thus, the Quantile regression estimator can be found as the solution to the following minimization problem: $\hat{\beta}_\theta = \arg_\beta \min \left(\sum_{i:y_i \succ x_i'\beta} \theta \left| y_j - x_i'\beta \right| + \sum_{i:y_i \prec x_i'\beta} (1-\theta) \left| y_i - x_i'\beta \right| \right)$ By minimizing a weighted sum of the absolute errors, the weights are symmetric for the median regression case ($\theta = 0.5$) and asymmetric otherwise. The former implies that the method is computationally straightforward while the latter implies that $\sqrt{n}\left(\hat{\beta}_\theta - \beta_\theta\right) \xrightarrow{d} N\left(0, \Omega_\theta\right)$, The CAPM presents $E_t\left(R_{i,t+1}\right) = \gamma_{1,t+1}\beta_{i,\tau}$ as $\tau < t + 1$. The beta-risk is determined over moving samples. The $\beta_{i,\tau}$ is the beta-risk obtained from a time series regression. $R_{i,\tau} = \alpha_i + \beta_{i,\tau} R_{m,\tau} + \mu_{i,\tau}$. The $R_{i,\tau}$ and $R_{m,\tau}$ are the excess return on the asset and the market portfolio, respectively.

2.4 The integrated Process

To test unit root, the raw daily sector index data are collected from Reuters, which includes 145,266 observations.

Comparing the alpha and beta in all estimators is investigated for maximum and minimum values. The parameters values at quantile 2.5% for minimum and quantile 97.5% for maximum will be shown for each sector in each market. The Quantile estimator, the State Space estimator, and Bayesian estimator are used for comparision. Particularly, the symmetry testing which is the less restrictive hypothesis of symmetry, for asymmetric least squares estimators, is applied to the Quantile regression case.

Here is a summary of the integrated Process.

Step1. Review the data, selecting the candidate models

Step2. Models decision based on the minimum and maximum of alpha and beta

Step3. Comparing the alpha and beta in all estimators

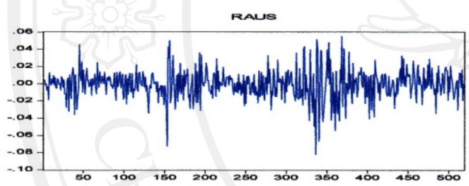
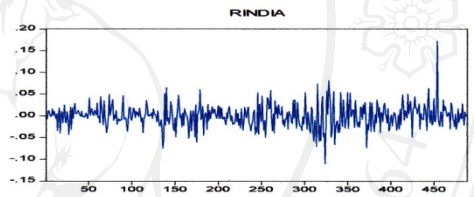
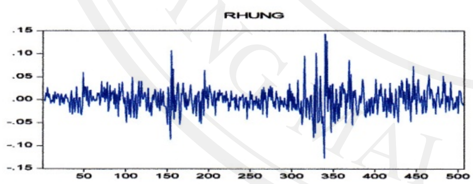
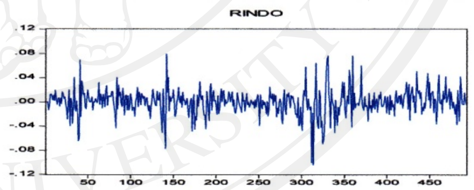
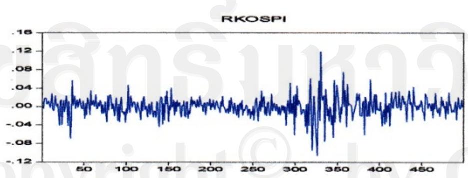
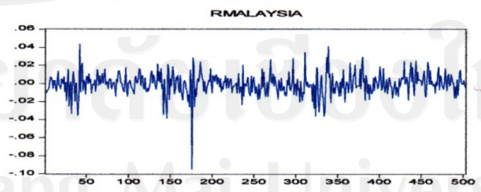
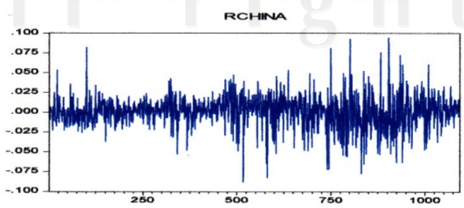
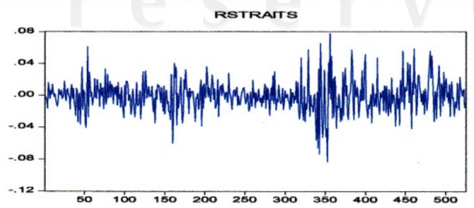
Step4. Comparing the parameters

Step5. Result illustration

3. Empirical Study

3.1 Data Description

The raw daily sector index data, Australian Securities Exchange (ASX), Bombay Stock Exchange (BSE), Hong Kong Stock Exchange (HKEX), Indonesia Stock Exchange (IDX), Korea Exchange (KRX), Kuala Lumpur Stock Exchange (KLSE), Shanghai Stock Exchange (SSE), Singapore Exchange (SGX), Taiwan Stock Exchange Corporation (TSEC), are collected from Reuters from June 19, 2007 to July 3, 2009. The Stock Exchange of Thailand (SET) is collected from Reuters from March 1, 1993 to July 30, 2009.

Australian Securities Exchange (ASX)	Bombay Stock Exchange (BSE)
	
Hong Kong Stock Exchange (HKEX)	Indonesia Stock Exchange (IDX)
	
Korea Exchange (KRX)	Kuala Lumpur Stock Exchange (KLSE)
	
Shanghai Stock Exchange (SSE)	Singapore Exchange (SGX)
	
The Stock Exchange of Thailand (SET)	Taiwan Stock Exchange Corporation (TSEC)

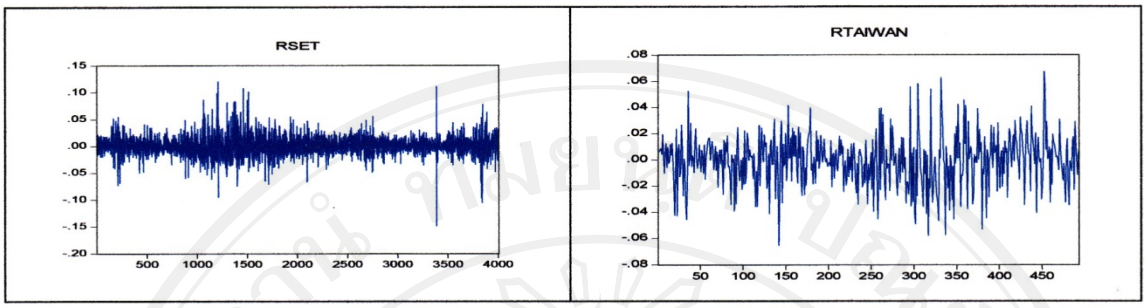


Figure 1. The Returns of Asia Stock Index

The ADF unit root tests for the all sector indexes, as well as their log differences (or rates of return). The original time series in logarithms are checked for stationary. In figure 1, it is clear that the sector indexes are non-stationary, while their rates of return are stationary. The results of the rates of return are stationary compared with the 1 % critical values to indicate rejection of the unit root null hypothesis.

The test of symmetry testing is the less restrictive hypothesis of symmetry, for asymmetric least squares estimators, but the approach is applied to the Quantile regression case. We may evaluate this restriction using Wald tests on the Quantile process. The Wald test formed for this null is zero under the null hypothesis of symmetry.

Table 1 shows the Quantile estimator that presents the highest time-varying alpha among portfolios in all Asian Stock Markets, with all values in the region of 0.0248 to 0.9206 of Plantation (PLANTATION) sector in the Kuala Lumpur Stock Exchange (KLSE), and Transport & Logistic (TL) sector in Stock Exchange of Thailand (SET) respectively. The lowest time-varying alpha among portfolios in all Asian Stock Markets are all in the region of -0.0238 to -0.0706 of Properties (PROPERTY) sector in the Kuala Lumpur Stock Exchange (KLSE), and Utilities (UTIL) sector in the Singapore Exchange (SGX) respectively.

The State Space estimator presents highest time-varying beta among portfolios in all Asian Stock Markets, with all values in the region of 1.2596 to 1.7443 of Information Technology (INFOR) sector in the Shanghai Stock Exchange (SSE), and HSCI-Energy (ENER) sector in Hong Kong Stock Exchange (HKEX) respectively. The Quantile estimator presents the lowest time-varying beta among portfolios in all Asian Stock Markets, with all values in the region of -0.3396 to 0.7406 of TECK (TECK) sector in the Bombay Stock Exchange (BSE), and Health Care (HEALTH) sector in the Shanghai Stock Exchange (SSE) respectively. The State Space estimator and Bayesian estimator show the closely value in the median.

The test of symmetry testing compares estimates at the 2.5% and 97.25% quartile with the median specification. The Bombay Stock Exchange (BSE) shows individual coefficient restriction test values even less evidence of asymmetry of Auto (AUTO), Bankex (BANKEX). The Hong Kong Stock Exchange (HKEX) shows The HSI - Com & Ind (COM), HSI – Finance (FIN), HSCI – Financials (FINB), HSCI - Prop & Con (PROP), HSI – Properties (PROPS) and HSCI – Tele (TELE). The Indonesia Stock Exchange (IDX) shows Agriculture (AGRI), Consumer (CONS), Financial (FIN), and Infrastructure (INFRA). The Korea Exchange (KRX) shows Banking - Miner, (BANKING), Construction, (CONSTR), Communication Service (CS), Electricity Gas (EG), Iron Steel Metal (ISM), Machinery (Mach), Paper Wood (PAPE), Securities – Miner (SECUR), Transportation Equipment (TE), Transport & Storage (TS), Textile, Wearing Apparel (TWA). The Kuala Lumpur Stock Exchange (KLSE) shows sectors of Construction (CONS), Consumer Products (CP), Industrial Products (IP), Plantation (PLANTATION), Properties (PROPERTY), and Technology (TECHNOLOGY). The Shanghai Stock Exchange (SSE) shows sectors of Consumer Staples (CONSTA), Financials (FINAN), Industrial Products (INDUS), and Telecom Services (TELE). The Singapore Exchange (SGX) shows sectors of Re Est H&D (ESTHD), Con Serve (SERV), Technology (TECH), Utilities (UTIL). The Stock Exchange of Thailand (SET) shows all sectors. The Taiwan Stock Exchange Corporation (TSEC) shows Bank and Insurance (BI), Biotech & Med Care (BMC), Cement (CEMENT), Chemical (CHEMICAL), Ele & Machinery (EM), Glass & Ceramic (GC), and Transportation (TRANS).

Table 1: The Maximum and Minimum Time Varying Coefficient of Alpha, Beta in CAPM Model

Countries/ Sectors/ Estimator	Alpha		Beta	
	Maximum	Minimum	Maximum	Minimum
Australian Securities Exchange (ASX)	0.0435	-0.0404	1.4876	0.3062
	Information Technology (INFORM)	Information Technology (INFORM)	Materials (MATERIALS)	Telecommunication Services (TELE)
	Quantile Estimator	Quantile Estimator	Quantile Estimator	Quantile Estimator
Bombay Stock Exchange (BSE)	0.0449	-0.0552	1.5143	-0.3396
	TECK (TECK)	Realty (REALTY)	Realty (REALTY)	TECK (TECK)

	Quantile Estimator	Quantile Estimator	Bayesian Estimator	Quantile Estimator
	0.0409	-0.0425	1.7443	0.1788
Hong Kong Stock Exchange (HKEX)	HSCI - Materials (MATE)	HSCI - Materials (MATE)	HSCI - Energy (ENER)	HSI - Utilities (UTIL)
	Quantile Estimator	Quantile Estimator	State-Space Estimator	State-Space Estimator
	0.0485	-0.0421	1.5109	-0.2241
Indonesia Stock Exchange (IDX)	Agriculture (AGRI)	Misc – Industry (MISC)	Mining (MIN)	Infrastructure (INFRA)
	Quantile Estimator	Quantile Estimator	Quantile Estimator	State-Space Estimator
	0.0442	-0.0409	1.6765	0.602
Korea Exchange (KRX)	Finance - Major (FINANCE),	Machinery (MACH)	Securities - Miner (SECUR)	Communication Service (CS)
	Quantile Estimator	Quantile Estimator	State-Space Estimator	State-Space Estimator
	0.0248	-0.0238	1.6507	-0.00001123
Kuala Lumpur Stock Exchange (KLSE)	Plantation (PLANTATION)	Properties (PROPERTY)	Consumer Products (CP)	Technology (TECHNOLOGY)
	Quantile Estimator	Quantile Estimator	State-Space Estimator	State-Space Estimator
	0.0382	-0.0287	1.2596	0.7406
Shanghai Stock Exchange (SSE)	Health Care (HEALTH)	Telecom Services (TELE)	Information Technology (INFOR)	Health Care (HEALTH)
	Quantile Estimator	Quantile Estimator	State-Space Estimator	Quantile Estimator
	0.0615	-0.0706	1.322	0.1087
Singapore Exchange (SGX)	Utilities (UTIL)	Utilities (UTIL)	Bas Mat (BASMAT)	Technology (TECH)
	Quantile Estimator	Quantile Estimator	State-Space Estimator	State-Space Estimator
	0.9206	-0.0365	1.3994	-0.0012
Stock Exchange of Thailand (SET)	Transport & Logistic (TL)	Petrochem, & Chemicals (PC)	Banking (BANKING)	Professional Services (PS)
	Quantile Estimator	Quantile Estimator	Quantile Estimator	Quantile Estimator
	0.0551	-0.0474	1.3719	-0.0442
Taiwan Stock Exchange Corporation (TSEC)	Tourism (TOURISM)	Tourism (TOURISM)	Cement (CEMENT)	Textile (TEXTILE)
	Quantile Estimator	Quantile Estimator	State Space Estimator	State Space Estimator

4. Conclusion

The investors often need to evaluate the risk in the stock market. Particularly, the global investors have to evaluate market for adjusting their portfolio. In this research, we use financial and econometric model base with time varying, State Space CAPM, Bayesian CAPM, Quantile regression CAPM. The alpha and beta values in ten Asian Stock Markets show the minimum and maximum values by aspect of CAPM model.

The highest time-varying alpha among portfolios in all Asian Stock Markets are presented by The Quantile estimator, with all values in the region of 0.0248 to 0.9206 and the lowest time-varying alpha among portfolios in all Asian Stock Markets with all values in the region of -0.0238 to -0.0706. The State Space estimator presents highest time-varying beta among portfolios in all Asian Stock Markets, with all values in the region of 1.2596 to 1.7443. The Quantile estimator presents the lowest time-varying beta among portfolios in all Asian Stock Markets, with all values in the region of -0.3396 to 0.7406. The State Space estimator and Bayesian estimator show the closely value in the median.

The test of symmetry testing compares estimates at the 2.5% and 97.25% quartile with the median specification. There are some sectors in Asian Stock markets showing individual coefficient restriction test values even less evidence of asymmetry. Except, The Stock Exchange of Thailand (SET) shows all values are less evidence of asymmetry in each sectors.

The key contribution of this paper is that we provide a financial and econometric model based on time varying, State Space CAPM, Bayesian CAPM, Quantile regression CAPM. In comparison with alpha and beta in CAPM model, our approach offer several advantages:

(1) The research offers initial knowledge about risk evaluation in time varying CAPM, which are required by global investors.
(2) The global investors have more information to evaluate their portfolio especially in ten Asian countries.
(3) We can compare the financial and econometrics model based on time varying estimators.

Acknowledgment:

We are grateful to the referees for many very useful comments and suggestions whic have greatly improved our draft. We are grateful to the editor for his insistence on standa errors and economic interpretation, which, although frustrating, made us try harder.

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