Chapter 4

Semi Parametric Estimation of ARFIMA Models of Asian Stock Indexes

The uncertain situation in 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. 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 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 m value of BSESN (Bombay SE Sensitive Index) Bombay Stock Exchange equals 1 that it has slop of the linear trend.

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

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.

Keywords: ARFIMA, SEMIFAR, Long memory fractional.

JEL classification codes:

C32; G11; G32

4.1 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 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. However, The Heterogenous Autoregressive (HAR) model is designed to model the behavior of the volatility inherent in financial time series. The model is able to describe simultaneously long memory, as well as sign and size asymmetries (McAleer and Medeiros (2008).

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.

4.2 Model Specifications

Long Memory Time Series

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

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

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

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

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

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

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:

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

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:

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

(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

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

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:

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

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).

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

where δ , $-1/2< \delta<1/2$ and m is the number of times that y_t must be differenced to achieve stationarity. The difference parameter is given by $d = \delta+m$. 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.

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

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

where $\delta \in (-0.5,0.5)$.

Estimation for SEMIFAR model Let

$\theta^{O} = \left(\sigma^{2}_{\in,O}, d^{O}, \phi^{O}_{1}, \ldots, \phi^{O}_{p}\right)^{t} = \left(\sigma^{2}_{\in,O}, \eta^{O}\right)^{t}$ 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* $|x| > 1, r \in \{0,1,2,...\}$, and $K(x) = 0$ *if* $|x| > 1$, $r \in \{0,1,2,...\}$ 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

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

(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

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

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 $\theta = (\sigma_\in^2, m+\delta, \phi_1, ..., \phi_p)^t$. Then $\hat{\theta}$ is defined by maximizing the approximate log-likelihood

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

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 $n \rightarrow \infty$, $\hat{g}$ 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

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

with $\theta_*^o = \left(\sigma_{\in,o}^2, \eta_*^o\right)^T = \left(\sigma_{\in,o}^2, \delta^o, \eta_2^o, \ldots, \eta_{p+1}^o\right)^T$. 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 $m^o = \left[d^o + 0.5\right]$ 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 $t = 1,\ldots,T$. The R/S statistic is defined as:

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

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:

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

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:

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

(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:

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

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 $0<\alpha<1$

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

where

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

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

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

(2.18)

It has a limiting standard normal distribution.

4.3 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

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

(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)

4.5 Data and Estimation

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.

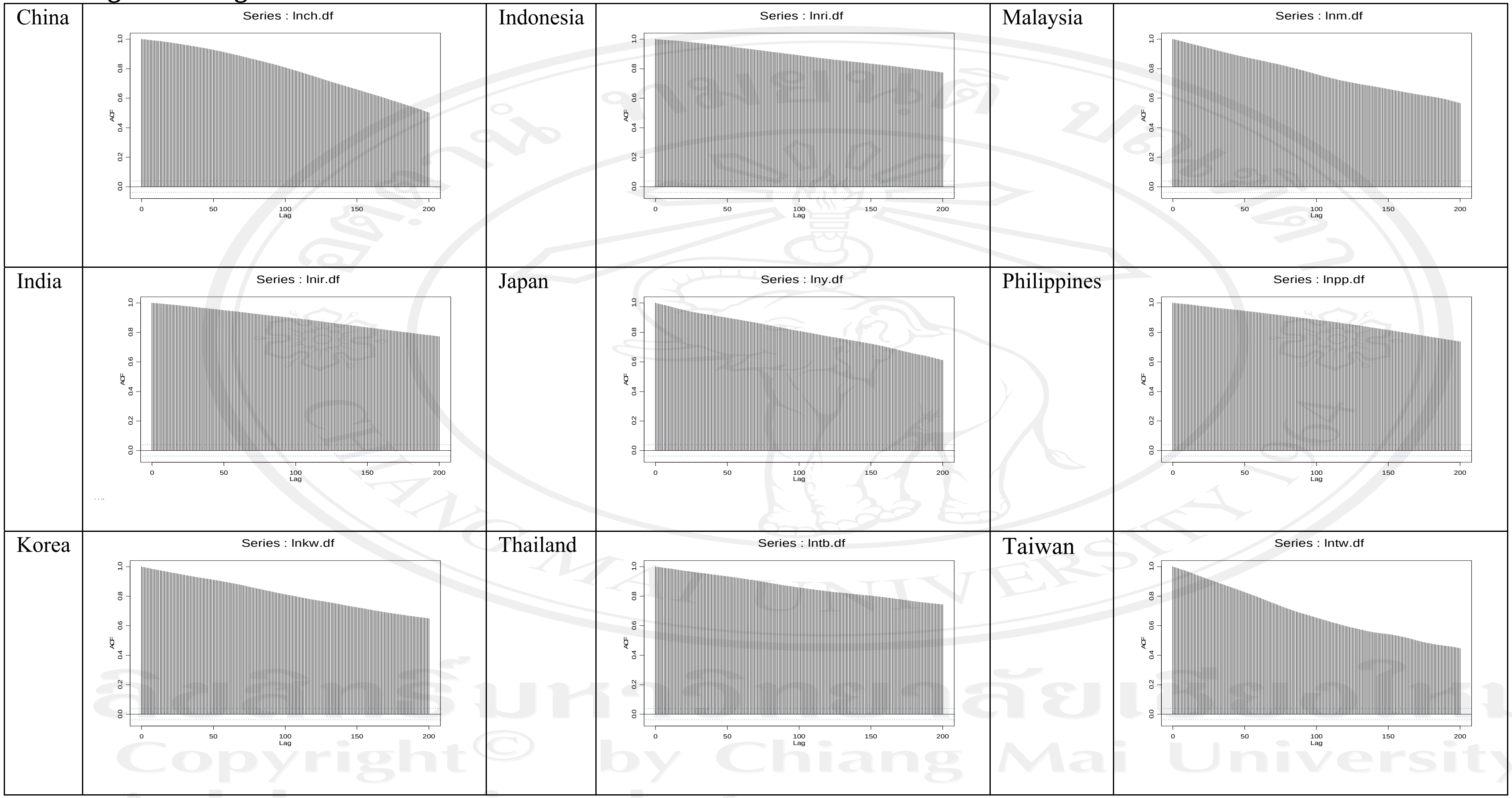


Figure 1 presents the autocorrelation of log daily Asia prices Index. The results show that the all indexes have long memory property in financial time series, consider the log daily Asia prices Index from November 10, 1998 to November 10, 2008. The autocorrelation of log daily Asia prices Index is highly 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 $\theta = 0$, 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.

4.6 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 $-1/2< \delta<1/2$ 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 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.

4.7 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. In this research, the Dynamic forecast method is used for prediction. Dynamic calculates multi-step forecasts starting from the first period in the forecast sample. In dynamic forecasting, previously forecasted values for the lagged dependent variables are used in forming forecasts of the current value. Static calculates a sequence of one-step ahead forecasts, using the actual, rather than forecasted values for lagged dependent variables, if available.

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

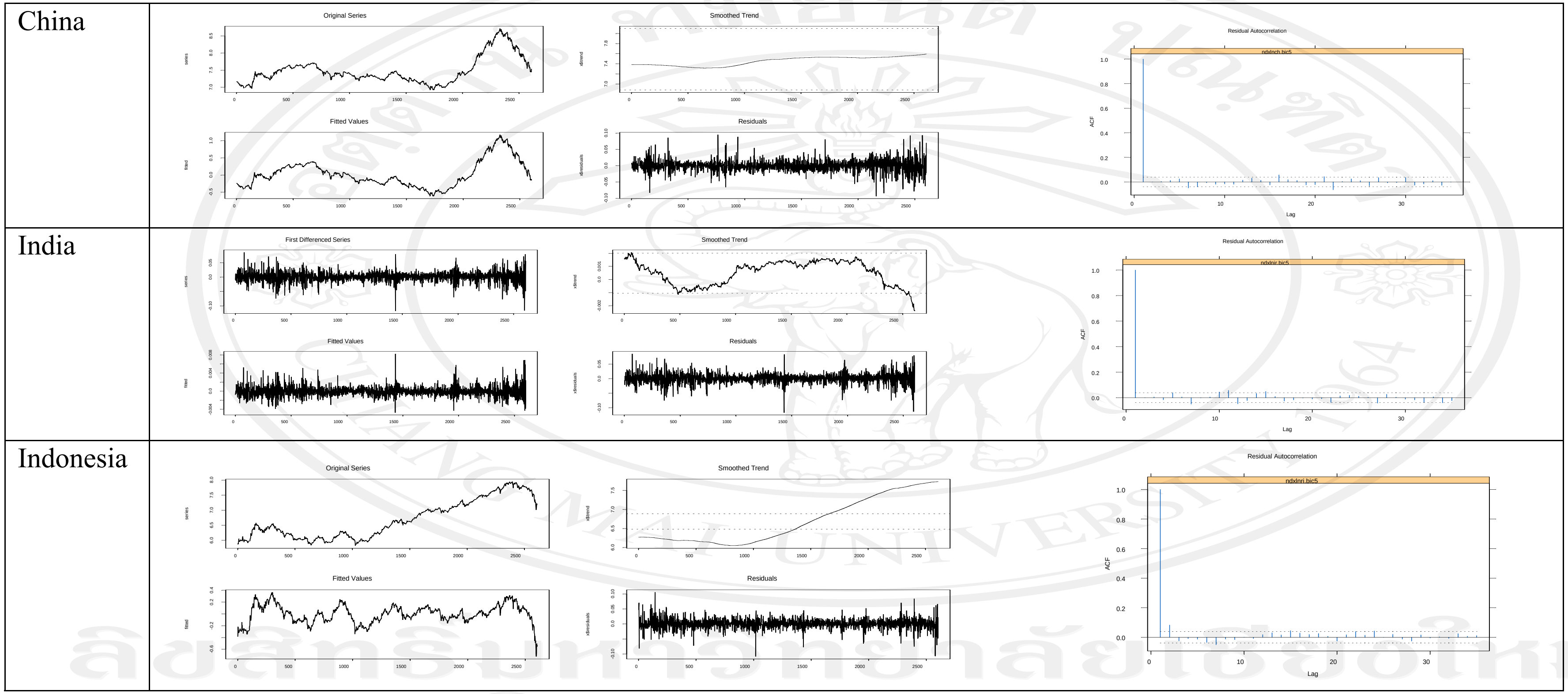


Figure 2: Diagnostic Test Asian Stock Index from SEMIFAR Model, Original Plot, Fitted Plot, Smoothed Trend Plot, Residuals Plot, Residuals Autocorrelation (Continued)

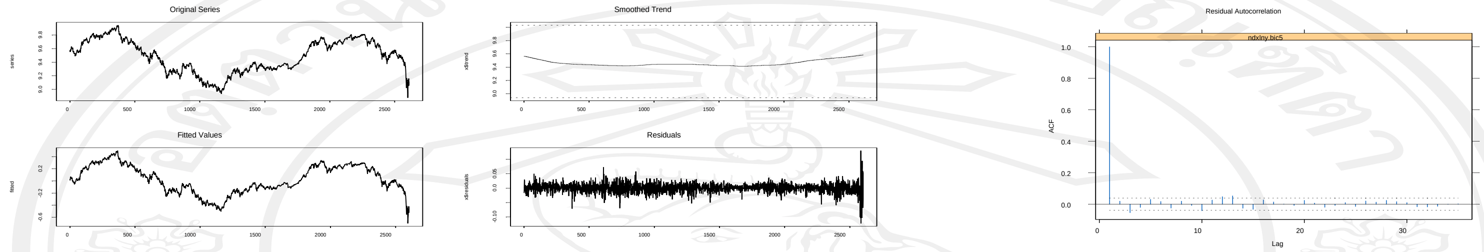
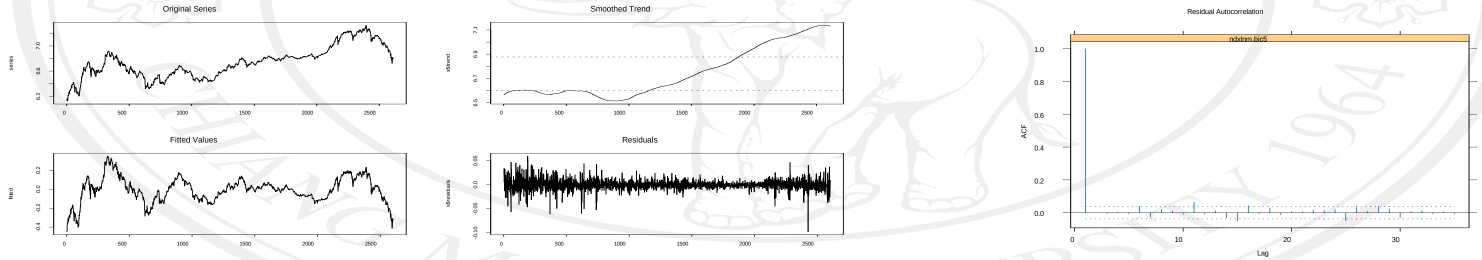
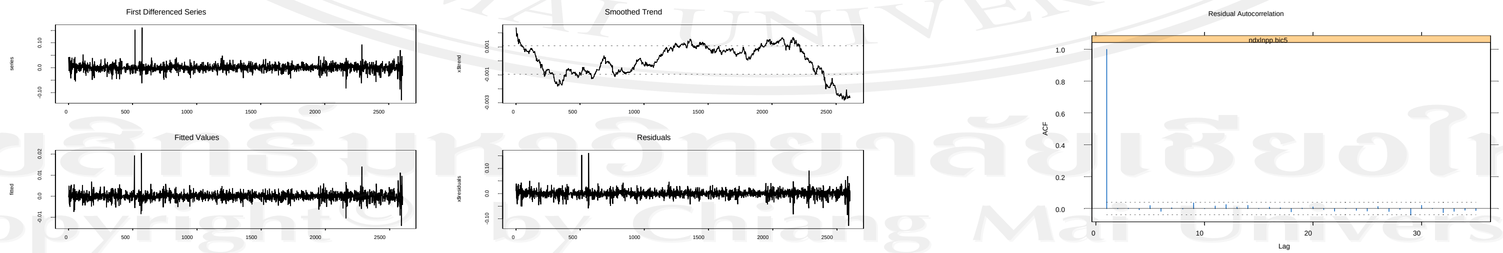
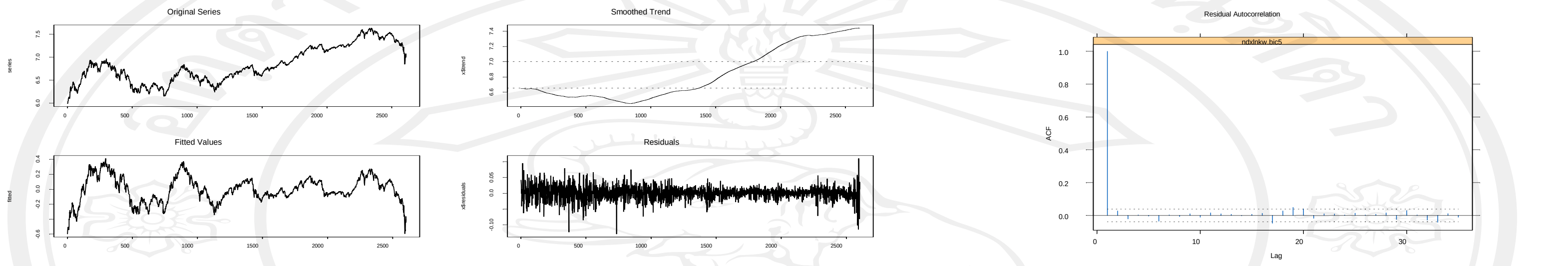
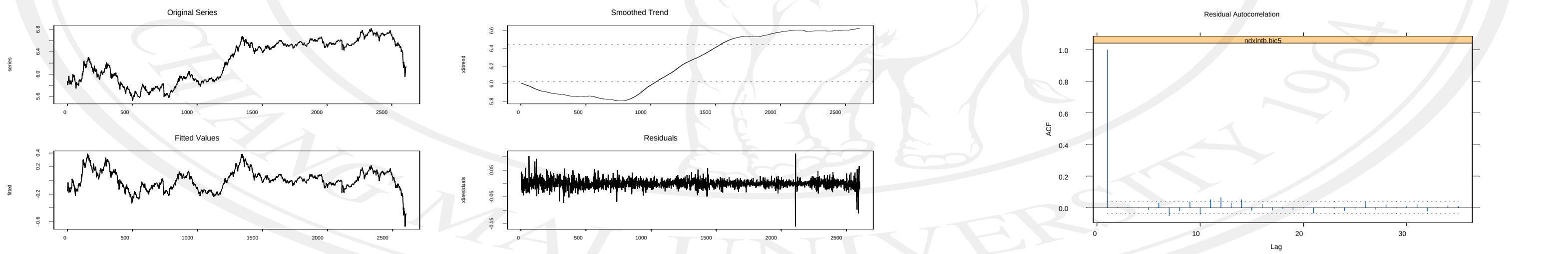
Japan	
Malaysia	
Philippines	

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

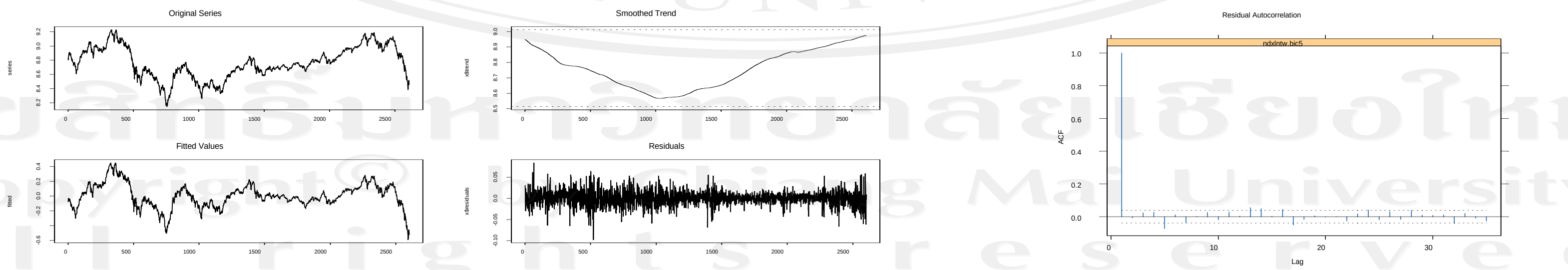
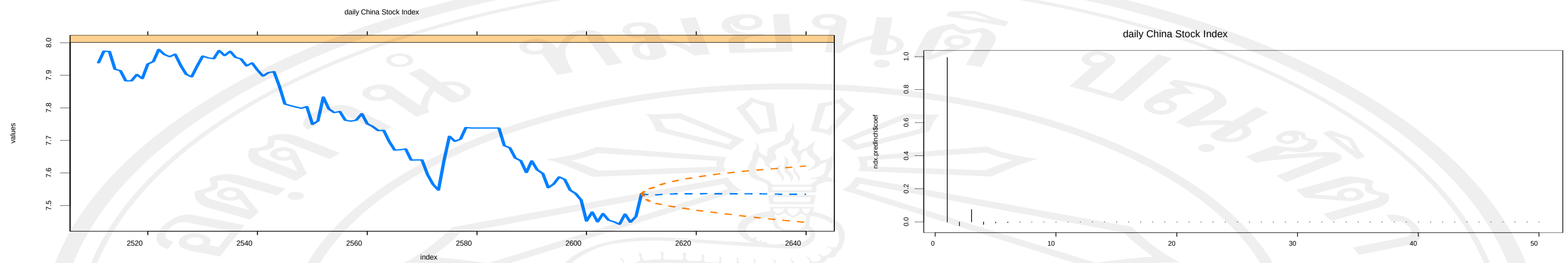
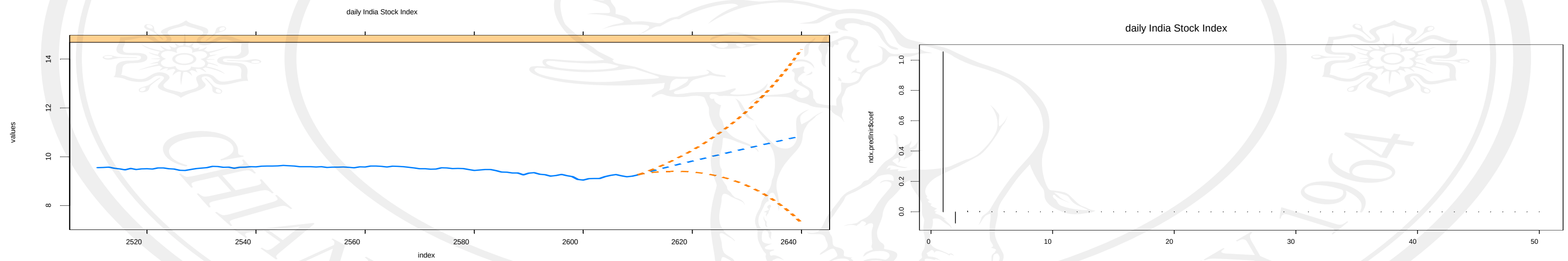


Figure 3: Plotted Asian Stock Index from SEMIFAR Model

china



India



Indonesia

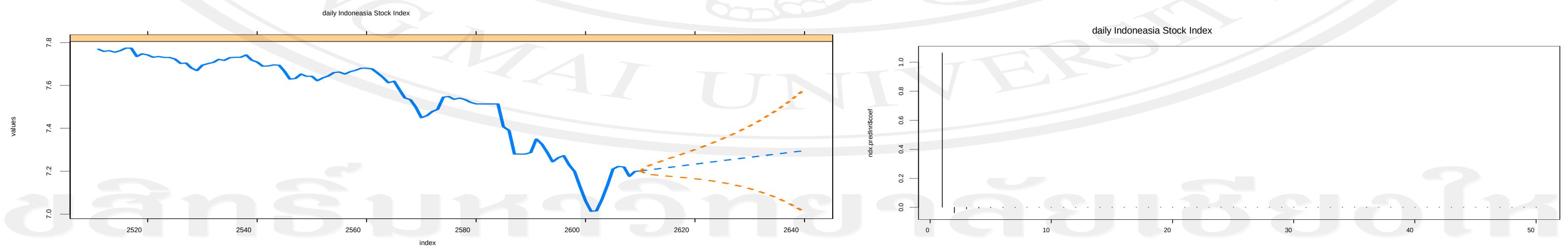
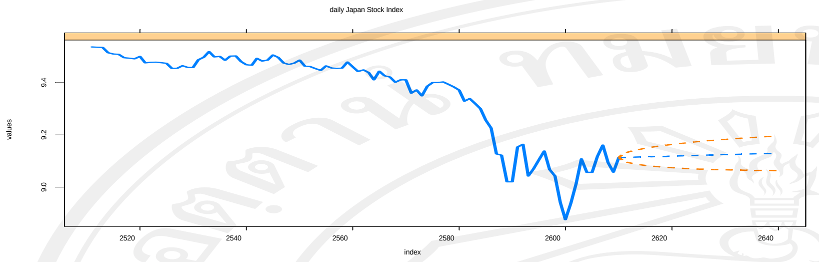
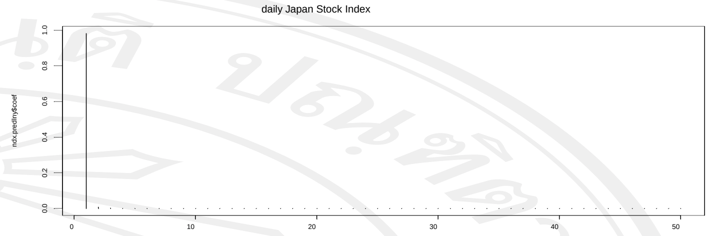


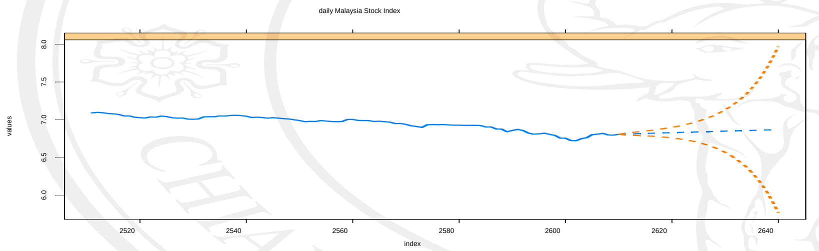
Figure 3: Plotted Asian Stock Index from SEMIFAR Model (Continued)

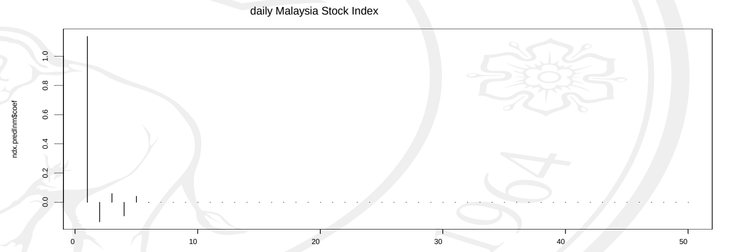
Japan



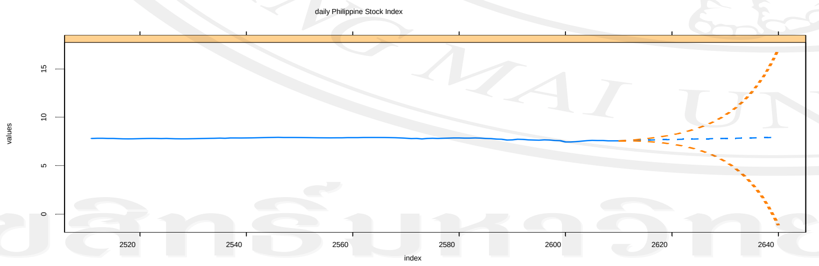


Malaysia





Philippine



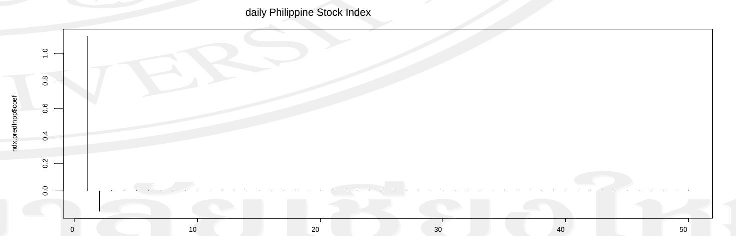
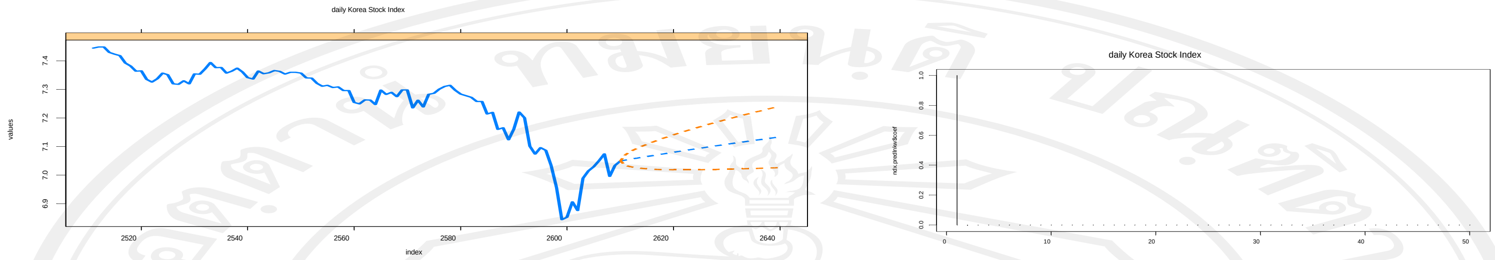
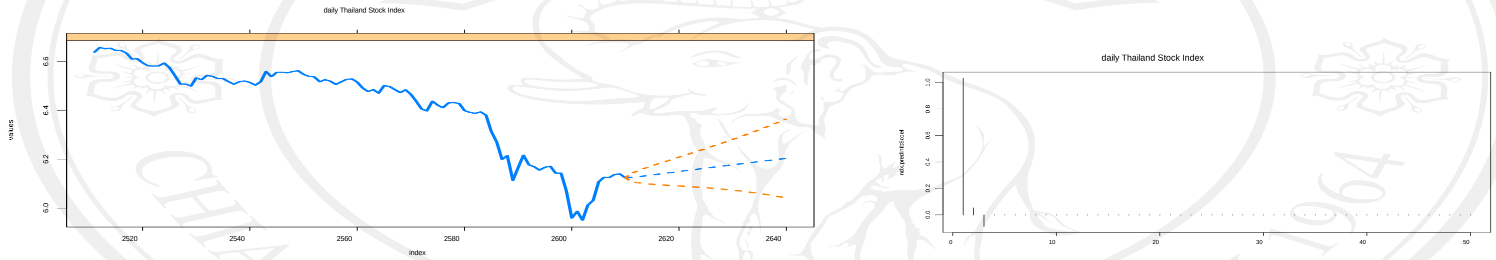


Figure 3: Plotted Asian Stock Index from SEMIFAR Model (Continued)

Korea



Thailand



Taiwan

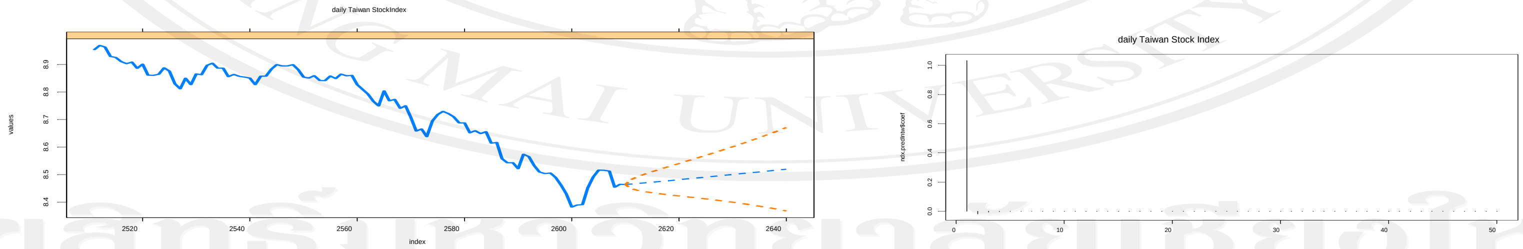


Table 4: The Prediction Value from SEMIFAR Model (next 30 periods)

Date	China	India	Indonesia	Japan	Malaysia	Philippines	Korea	Thailand	Taiwan
29/12/2008	1869.64	11179.09	1344.93	9082.46	905.96	1966.87	1156.21	457.42	4747.15
30/12/2008	1864.41	11847.83	1349.24	9086.09	908.41	1995.20	1159.80	457.97	4754.75
31/12/2008	1869.08	12544.03	1353.57	9090.63	911.05	2022.93	1163.40	459.21	4762.37
1/1/2009	1871.32	13271.84	1357.91	9096.09	912.60	2050.42	1167.01	460.49	4770.47
2/1/2009	1872.26	14033.46	1362.26	9101.55	914.61	2077.67	1170.52	461.79	4779.06
3/1/2009	1873.19	14829.89	1366.63	9106.10	916.53	2104.64	1174.03	463.13	4787.67
4/1/2009	1873.76	15666.81	1371.01	9111.57	918.37	2131.54	1177.56	464.43	4796.30
5/1/2009	1874.13	16542.70	1375.40	9117.04	920.30	2158.35	1180.98	465.77	4804.94
6/1/2009	1874.51	17460.56	1379.81	9122.51	922.23	2185.06	1184.53	467.08	4814.08
7/1/2009	1874.88	18423.83	1384.23	9127.98	924.17	2211.66	1187.97	468.39	4822.75
8/1/2009	1875.07	19434.40	1388.67	9132.55	926.02	2238.14	1191.42	469.75	4831.92
9/1/2009	1875.44	20494.26	1393.12	9138.03	927.97	2264.71	1194.76	471.07	4841.11
10/1/2009	1875.82	21605.43	1397.58	9143.51	929.92	2291.13	1198.23	472.34	4850.32
11/1/2009	1875.82	22774.57	1402.06	9148.09	931.78	2317.63	1201.59	473.66	4859.54
12/1/2009	1875.63	23999.78	1406.56	9153.58	933.65	2344.44	1204.96	474.99	4868.79
13/1/2009	1875.44	25285.84	1411.07	9159.07	935.61	2371.08	1208.34	476.28	4878.05
14/1/2009	1875.26	26635.49	1415.59	9164.57	937.48	2397.78	1211.60	477.61	4887.32
15/1/2009	1874.88	28051.57	1419.98	9169.15	939.36	2424.55	1215.00	478.90	4896.62
16/1/2009	1874.51	29537.03	1424.53	9174.65	941.24	2451.36	1218.29	480.20	4905.93
17/1/2009	1874.32	31094.93	1428.96	9180.16	943.13	2478.48	1221.58	481.50	4915.26
18/1/2009	1873.94	32728.45	1433.54	9184.75	945.01	2505.39	1224.88	482.80	4924.61
19/1/2009	1873.57	34444.34	1437.99	9189.35	946.81	2532.60	1228.07	484.06	4933.97
20/1/2009	1873.19	36242.94	1442.45	9194.86	948.71	2559.58	1231.39	485.36	4943.36
21/1/2009	1872.82	38127.84	1446.93	9199.46	950.61	2586.60	1234.60	486.63	4952.76
22/1/2009	1872.63	40102.74	1451.42	9204.06	952.41	2613.90	1237.81	487.89	4962.18
23/1/2009	1872.26	42175.72	1455.93	9209.58	954.23	2640.70	1240.91	489.21	4971.61
24/1/2009	1872.26	44346.98	1460.45	9213.27	956.14	2667.77	1244.14	490.49	4981.57
25/1/2009	1872.07	46620.70	1464.98	9217.88	957.95	2694.59	1247.25	491.76	4991.04
26/1/2009	1872.07	49006.10	1469.53	9222.49	959.78	2721.40	1250.38	493.00	5000.53
27/1/2009	1871.88	51508.39	1473.95	9227.10	961.60	2747.92	1253.51	494.28	5010.04

4.8 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.

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.