ON THE FORECASTABILITY OF ASEAN-5 STOCK MARKETS RETURNS USING TIME SERIES MODELS

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Abstract

This study examines the forecastability of ASEAN-5 stock market returns using linear and non-linear time series models. Time series models with GARCH errors are also considered. Based on formal econometrics tests, this study shows that the behaviour of these returns do not follow random walk movement. Results of this study also reveal that all the estimated time series models, both linear and non-linear, have smaller out-of-sample forecast errors than the random walk model. These two findings robustly indicate that returns of ASEAN-5 stock markets do not follow random walk movement and are forecastable. Thus, this study can be taken as providing justification for the work of technical analysts.

Keywords: Random walk; Time series models; Autoregressive; Smooth Transition Autoregressive; GARCH; Forecasting; ASEAN-5 stock markets.

I. INTRODUCTION

Over the past few decades, there has been a growing interest in the modelling and forecasting of economic and financial variables, such as GDP, exchange rates, stock prices or returns. Most of these earlier works used structural models, trying to explain the fluctuations in the variable under study with some exogenous macroeconomic variables as the explanatory variables. Lately, with the advancement of time series econometric techniques, many researchers resort to time series models in their forecasting endeavour. This approach gain further popularity when data of higher frequency are becoming available from the equity, foreign exchange and derivatives markets, which is particularly useful to those with short-term horizons.

Time series models have been widely applied in forecasting financial time series for several reasons. The most important reason is that time series models enjoy greater simplicity as compared to the econometric structural models without loosing their forecastability. In other words, the forecasting performance of time series models are at least comparable to structural models disregarding the fact that the former requires minimum information set. Unlike a structural model, a time series model demands nothing more than the historical records of the variable under investigation[1]. It is assumed that the movements of a time series are solely explained in terms of its own past and therefore forecasts can be made by extrapolation of the past (Harvey, 1993). The work of time series modelling and forecasting has close connection

[1] One problem encountered by forecasters using structural models is that the explanatory variables introduced on the right-hand side of the equations make them difficult to use for projection (Six, 1989). It is the simplicity of the time series requirement that enables the resulting model to be a good alternative to the solution of many forecasting problems.

with technical analysis, which basically involves the study of past price behaviour in order to draw conclusions concerning the direction and magnitude of future price movements. From the practical aspect, there is a growing trend that financial market participants use price histories to make predictions of future values. For example, interviews reported in Taylor and Allen (1992) showed that at least 90% of the respondents used technical analysis in forming their expectations. There is also encouraging evidence suggesting that forecasting using technical analysis is able to produce surprisingly accurate forecasts (see, for example, Pruitt and White, 1988, 1989; Brock *et al*., 1992). Even in the area of non-linear forecasting, it was seen by many technical traders as justification for their work. Clyde and Osler (1997) argued that technical analysis can be viewed as a simple way of exploring the non-linear behaviour of financial time series. For example, rules such as "head and shoulders" are clearly attempting to find some kind of non-linearity in these series.

Linear time series model was first formally introduced by Yule in 1926, in the form of autoregressive (AR) model, even though time series analysis is believed to have started much earlier (Cryer, 1990). Since then, time series models have gained its popularity within the empirical regularities. Recently, non-linear time series models have been introduced to cater for the need of characterizing the nonlinear dynamics of certain variables in various fields. For instance, Threshold Autoregressive (TAR) model was introduced to characterize the limit cycles and cyclical data (Tong and Lim, 1980) and Smooth Transition Autoregressive (STAR) model was developed to characterize the non-linearities in business cycles (Teräsvirta and Anderson, 1993). The latter has been widely adopted in the study of non-linearities in various financial time series data, particularly onto the exchange rates.

The main objective of this study is to examine the forecastability of ASEAN-5 stock market returns, utilizing linear and non-linear time series models. This study is motivated by the following reasons. First, previous published studies on the ASEAN-5 stock markets are largely focused on fundamental analysis based on the Efficient Market Hypothesis (EMH), Arbitrage Pricing Theory (APT) and Capital Asset Pricing Model (CAPM) but the technical analysis has been sidelined for pure academic purposes. This study is therefore conducted to fill in this literature gap. Second, this study aims to investigate the applicability of time series models in the ASEAN-5 stock markets in terms of asset returns forecasting. Stock prices were long believed to follow a geometric random walk with uncorrelated innovations. The unpredictable and random behaviour of stock market continue to be scrutinized by researchers (see, for example, Fama, 1976; Fama and French, 1988; Lo and MacKinlay, 1988; Dockery and Kavussanos, 1996; Zhu, 1998). Suppose time series model is capable of generating future asset prices or returns movements with acceptable accuracy[2], this indicates that the series are not random and thus forecastable, which will have strong implication on weak-form efficiency[3]. Besides that, stock market forecasters may have reliable forecasts from alternative source—technical analysts—almost instantaneously and at cheaper cost.

In this study, we employ the linear autoregressive (AR) model and non-linear Smooth Transition Autoregressive (STAR) model. As forecasters are always interested to evaluate the gain in the performance of their forecasting models over the random walk, this study also generated the random walk forecasts. Besides that, the Generalized Autoregressive

[2] Accuracy is the primary criterion in selecting forecasting techniques, and this is supported by the survey conducted by Yokum and Armstrong (1995). They found that "accuracy" is the dominant criterion among all the forecasting experts in their sample (researchers, educators, practitioners and decision makers).

[3] A random walk series implies that the market is weak-form efficient. Since new information is deemed to come in a random fashion in an efficient market, changes in prices that occur as a consequence of that information will seem random. Thus, investors in weak-form efficient market cannot expect to find any patterns in the historical sequence of stock prices that will provide insight into future price movements and allow them to earn abnormal rate of return.

Conditional Heteroscedasticity (GARCH) model, which is commonly adopted in stock market study are also incorporated in our time series models for the forecasting evaluation.

The remainder of this paper is organized as follows: Section II provides an overview of the time series models used in this study. Section III contains the preliminary data analysis explains the research design in this study. The results on the forecasting performance of various models are discussed in Section IV. The final section concludes this study.

II. AN OVERVIEW OF THE TIME SERIES MODELS

Autoregressive model of order *p* or briefly AR(*p*) of a time series y_t could be represented by the general equation:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i (y_{t-i} - u) + \varepsilon_t \qquad (1)$$

where α_0 and α_i ; i = 1, ..., *p* are autoregressive parameters to be estimated, *u* refers to the mean value of y_t, and ε_t represents random errors with zero mean and finite variance.

This linear time series model has been extended to a non-linear time series model by adding a nonlinear component to Equation (1). The resulting model, known as the Smooth Transition Autoregressive (STAR) model allows the variable under investigation to adjust smoothly every moment within different regimes with the speed of adjustment depends on the size of the deviations from its equilibrium level. STAR of order *p* or briefly STAR(*p*) representation is given by (see Teräsvirta and Anderson, 1993):

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i (y_{t-i} - u) + \left[\sum_{i=1}^{p} \beta_i (y_{t-i} - u) \right] \mathrm{F}(y_{t-d}) + \varepsilon_t \qquad (2)$$

where α_0 and α_i ; i = 1, ..., *p* stand for autoregressive parameters; β_i ; i = 1, …, *p* are known as nonlinear autoregressive parameters. F( ) is the transition function depending on the lagged level, y_{t-d} where *d* is known as the delay length or delay parameter, and ε_t is a white noise with zero mean and constant variance.

Two versions of transition functions, namely the exponential and logistic functions are proposed in the literature. These functions, in that order, can be expressed as

$$\mathrm{F}(z_{t-d}) = 1 - \exp[-\gamma^2 (z_{t-d})^2] \qquad (3)$$

and

$$\mathrm{F}(z_{t-d}) = [1 - \exp(-\gamma^2 z_{t-d})]^{-1} \qquad (4)$$

where γ^2 stands for the transition parameter, measuring the speed of adjustment.

STAR model (2) with specification (3) is known as LSTAR or logistic STAR model, whereas with specification (4) is termed ESTAR or exponential STAR model[4]. Practically, these two

[4] Interested readers could refer Teräsvirta and Anderson (1993) and Teräsvirta (1994) for thorough discussion on the theoretical and empirical aspects of these models.

models have quite different empirical implications on the stock market behaviour: the LSTAR model describes the asymmetrical nonlinear adjustment process, while the ESTAR model suggests symmetrical nonlinear adjustment process.

Note that the assumption that ε_t is a white noise in Equations (1) and (2) is usually violated in the modelling of financial time series, which is well-known for their volatile behaviour. Engle (1982) incorporates the time-varying variance by specifying

$$\varepsilon_t = z_t \sigma_t \tag{5}$$

where z_t ~ i.i.d. (0, 1) and σ_t is a time varying, positive, and measurable function of the time t – 1 information set. In formulating his ARCH (q) model, Engle (1982) proposed the time-varying parameter σ_t as dependent of past values of ε_t, represented by the form:

$$\sigma_t^2 = \partial_0 + \sum_{i=1}^{q} \partial_i \varepsilon_{t-i}^2 \tag{6}$$

where $\partial_0 > 0$ and $\partial_i \geq 0$.

In practice, the linear ARCH (q) models usually require a long lag length q. It is well known that longer lag length might reduce the degree of freedom. The Generalized ARCH or GARCH (p, q) model due to Bollerslev (1986) provides an alternative with more flexible lag structure. The GARCH (p, q) model is represented by

$$\sigma_t^2 = \partial_0 + \sum_{i=1}^{q} \partial_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \theta_i \sigma_{t-i}^2 \tag{7}$$

A special case of GARCH (p, q) model with $p = q = 1$ namely the GARCH (1, 1) model was independently suggested by Taylor (1986). To ensure a well-defined process in the context of GARCH (1, 1) model, the following customary constraints are applied to the parameters: $\partial_i >$ 0; i = 0, 1, $\theta_1 > 0$ and $\partial_1 + \theta_1 < 1$. In most applications, GARCH (1, 1) model is found suffice. Hence, this study will confine to the use of GARCH (1, 1) model.

III. DATA AND RESEARCH METHODOLOGY

The Data

The daily Composite Indices of the five major ASEAN stock markets, covering the period of 2/1/1990 to 31/10/2001, amounting to a total of 3087 observations are employed in this study. Specifically, the data consist of daily closing prices of Jakarta Composite Index (Indonesia), Kuala Lumpur Composite Index (Malaysia), Philippines Composite Price (the Philippines), Strait Times Index (Singapore) and Stock Exchange of Thai (Thailand). In this study, the sample is divided into two sub-periods. The first sub-period ranging from 2/1/1990 to 31/10/2000 is used in the model estimation and the remainder is kept for the purpose of out-of-sample forecasting accuracy evaluation. The data set is obtained from Kuala Lumpur Stock Exchange (KLSE) and the indices are denominated in local currency units.

The returns of stock indices are computed as percentage returns (r_t), using the relationship:

$$r_t = 100 * \ln(P_t / P_{t-1}) \tag{1}$$

where P_t is the closing price of stock index on day *t*, and P_{t-1} the price stock index on the previous trading day.

The resulting returns are plotted in Figure 1. From this figure, it can be observed that all the ASEAN-5 stock returns are fluctuating around the zero horizontal line, indicating that on average the returns are zero. This shows that the major stock markets in the ASEAN region are self-correcting and every chance of abnormal profits is arbitraged away.

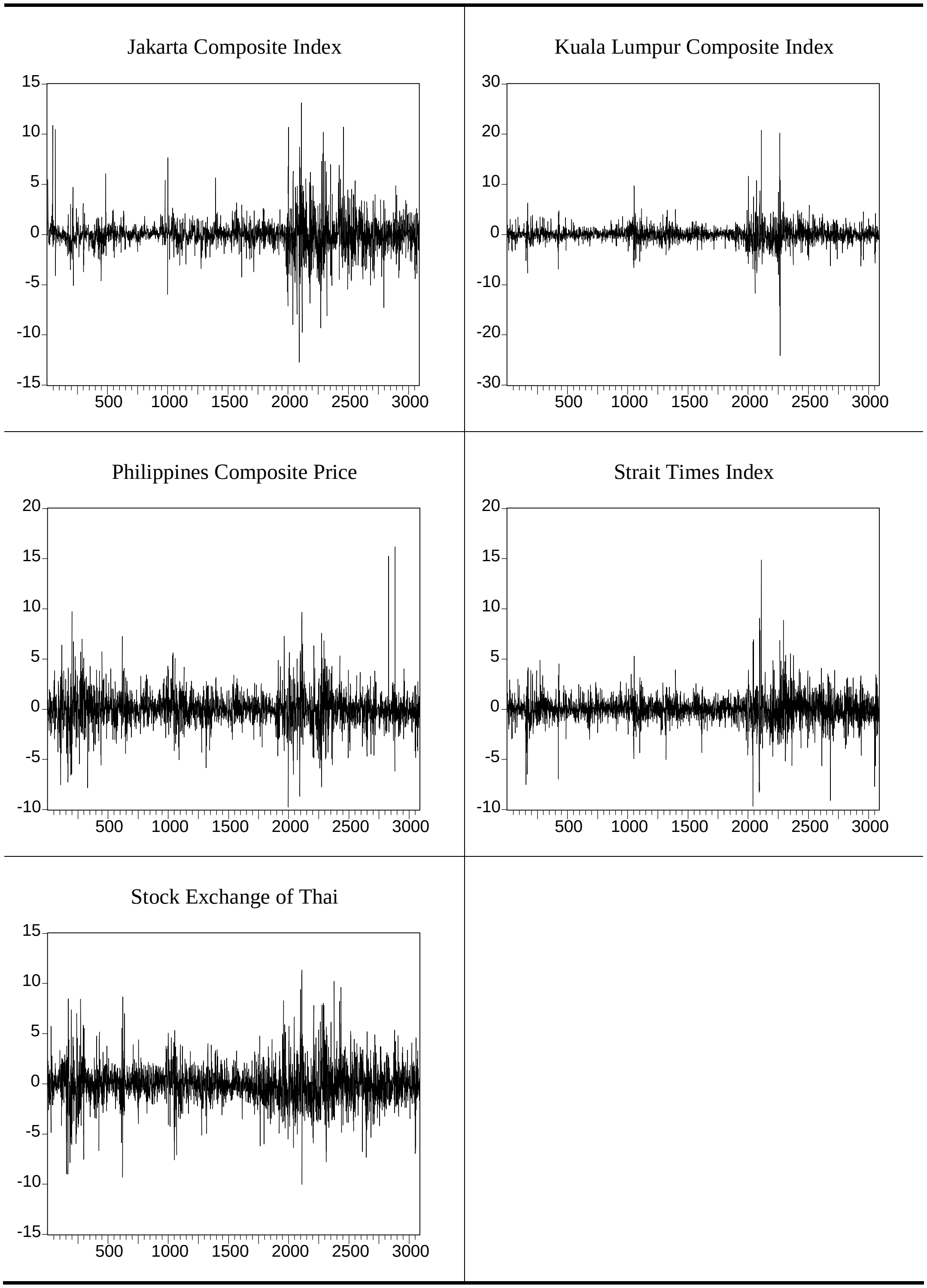
One requirement in the time series modelling is that the series must be stationary. To investigate the stationarity property of the returns series, formal augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are utilized in this study. The results of conducting such tests are summarized in Table 1. As the returns series have zero mean and trendless as depicted in Figure 1, we proceed with the testing of unit root in the absence of intercept and trend. Both the ADF and PP test statistics in Table 1 suggest that the returns series as represented by y_t are stationary at 1% significance level in all cases.

Table 1
Unit Root Tests Results

Composite Index	**ADF**		**PP**	
	y_t	Δy_t	y_t	Δy_t
Jakarta Composite Index	–23.825	–40.302	–45.147	–144.813
Kuala Lumpur Composite Index	–23.984	–41.057	–51.667	–165.315
Philippines Composite Price	–23.407	–40.463	–45.904	–141.199
Strait Times Index	–24.613	–41.203	–47.079	–143.761
Stock Exchange of Thai	–23.318	–40.446	–48.616	–154.349

Notes: y_t and Δy_t stands for the level and first-difference of returns series respectively. The critical values for ADF and PP tests with no constant and no trend are identically –2.567, –1.939 and –1.615 for 1, 5, and 10% significance level.

Figure 1
Plots of ASEAN-5 Stock Markets Returns



We note here that there is a chance that y_t follows a random walk process and in fact stock prices were long believed to follow a geometric random walk with uncorrelated innovations. Recall that if Δy_t or the first-difference of y_t is purely a white noise, then it follows that $y_t = y_{t-1}$. In other words, y_t would then be a random walk process. Hence, by checking the property of Δy_t, we would be able to verify whether y_t is a random walk or not.

Our unit root tests results in Table 1 suggest that Δy_t is stationary at significance level. We then conduct the portmanteau Q-test to check whether the stationary series are actually identically and independently distributed (Brockwell and Davis, 1996). Briefly, the null hypothesis in the Q-test is that the sample autocorrelation of all lags are statistically indifferent from zero, implying that Δy_t is i.i.d. The test results for the computed Q-statistics up to 12, 24 and 36 lags are reported in Table 2. It is obvious from this table that the null of white noise for the first-difference series of the returns has been strongly rejected in all cases. Thus, this study has demonstrated through formal econometric test procedures that the returns series are not random walk movement at all. To sum, we have shown that the returns series are stationary, which does not move in random walk manner. We thus model these series with the linear and non-linear time series models as discussed in Section II.

Table 2
Q-Statistics for Δy_t

	Lags		
	12	**24**	**36**
Jakarta Composite Index	563.620*	616.290*	664.370*
Kuala Lumpur Composite Index	857.510*	914.950*	927.930*
Philippines Composite Price	533.260*	562.160*	611.670*
Strait Times Index	547.480*	568.630*	582.390*
Stock Exchange of Thai	623.370*	650.340*	680.320*

Note: Asterisk (*) indicates significance at 1% significance level.

Research Methodology

This study models the ASEAN-5 stock markets returns with AR(p) and STAR(p) models with the assumption that the residuals ε_t follow white noise process. Two type of STAR models namely the ESTAR(p) and LSTAR(p) as described in the aforementioned section are considered here, with p =1 in all cases, as suggested by the sample partial autocorrelation functions (PACF) in Figure 2. For the purpose of forecasting comparison, we also allow ε_t to follow GARCH (1, 1) process, yielding AR(1)-GARCH(1, 1), LSTAR(1)-GARCH(1, 1) and ESTAR(1)-GARCH(1, 1) models. Thus, a total of six time series forecasting models for each returns series are considered in this study. These six models and a random walk model are utilized to generate out-of-sample forecast for the forecast horizons of 1 day, 1 week, 1 month, 3 months, 6 months, 9 months and 1 year for each returns series, starting from 1/11/2000. The forecasting performance of these models on each forecast horizon is evaluated using the root mean squared error (RMSE)[5]. The results of contrasting the out-of-sample performance are discussed in the following section.

IV. OUT-OF-SAMPLE FORECASTING PERFORMANCE

The out-of-sample performances of the various time series forecasting models, including the random walk model are summarized in Table 3. Based on this table, we are able to evaluate whether the returns of the ASEAN-5 stock markets can be predicted by time series models, or they are just unpredictable random movements. In addition, the ranking of the forecasting models based on RMSE for each forecast horizon is given in Table 4. From this table, we are able to further contrast the forecast performance of models on the basis of the nature of linearity (linear versus non-linear), assumption of errors (normal errors versus GARCH errors) and specification of STAR models (ESTAR versus LSTAR). To simplify our comparison exercise, we average out the ranking of each model across countries. Note that the model with better performance will have smaller average value.

Time Series Models versus Random Walk Model

Table 3 shows that the RMSE values of random walk models are substantially greater than all time series models considered in the current study, for all horizon across all countries. In other words, the random walk model ranked last in all cases, with the only exception of 1-week horizon for the returns of Strait Time Index, in which the random walk managed to ranked second among all seven models under study. This implies that the random walk model is easily beaten by any time series model under study. This finding reinforces our earlier finding that the returns of ASEAN-5 stock markets do not follow random walk movements, or else they will not be forecastable by the time series models.

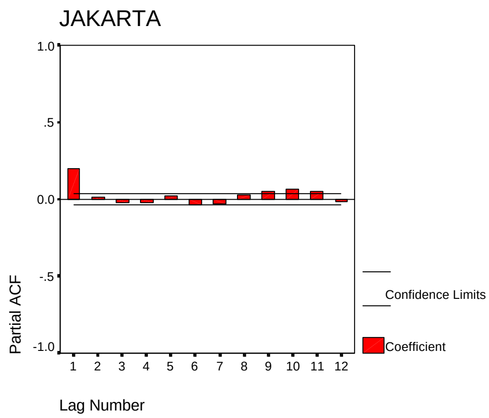
Linear versus Non-linear

In this exercise, linear models as represented by the AR (1) and AR (1) – GARCH (1, 1) models, are found to be superior to non-linear models, on average, for forecast horizon of 1 months and longer period (Table 4). For instance, the average rank of best linear model for 1-month forecast horizon is first (ARG model), whereas the average rank of the best non-linear model in this horizon is third (ESTARG model). However, for forecast horizon of 1 week, linear models are at most comparable with non-linear models, whereas the former lost its competitiveness to the latter models in the 1-day forecast horizon. Thus, although there is evidence of non-linearity on stock returns (Tse, 2001), information on non-linearity seems to produce no gain in the prediction of stock returns. However, one must not be too pessimistic in this regard as the performance of other variants of nonlinear models such as STAR error correction (STAR EC) model (Tse, 2001) and smooth transition GARCH or STGARCH model (Lundbergh and Teräsvirta, 1998) remain unrevealed to date.

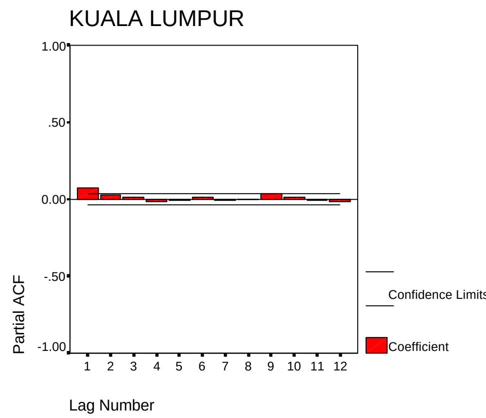
[5] The other two commonly used criteria are mean absolute percentage error (MAPE) and mean absolute deviation (MAD).

Figure 2
Plots of Partial Autocorrelation Functions (PACF)

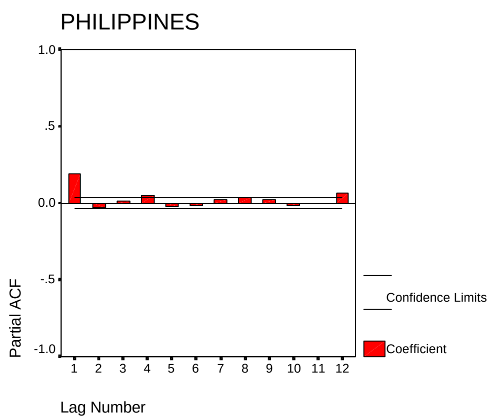
Jakarta Composite Index



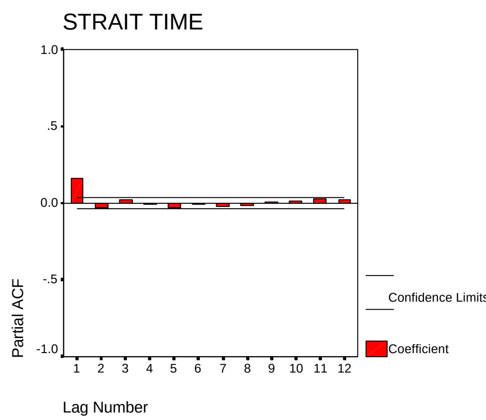
Kuala Lumpur Composite Index



Philippines Composite Price



Strait Times Index



Stock Exchange of Thai

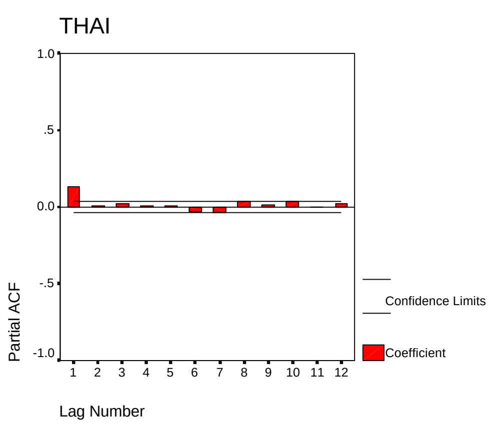


Table 3
Forecasting Performance by the RMSE

Forecast Horizon	**RMSE**						
	RW	AR	ARG	ESTAR	ESTARG	LSTAR	LSTARG
				Jakarta Composite Index			
1 Year	1.854	0.001	0.006	0.029	0.009	0.025	0.009
9 Months	1.826	1.342	1.342	1.349	1.344	1.349	1.344
6 Months	1.779	1.062	1.061	1.069	1.064	1.069	1.064
3 Months	2.079	1.638	1.639	1.635	1.637	1.635	1.637
1 Month	1.431	1.430	1.432	1.434	1.433	1.434	1.433
1 Week	1.264	1.403	1.403	1.403	1.403	1.403	1.403
1 Day	1.480	1.414	1.414	1.413	1.413	1.413	1.413
				Kuala Lumpur Composite Index			
1 Year	1.789	1.296	1.299	1.295	1.298	1.295	1.297
9 Months	1.706	1.343	1.346	1.341	1.345	1.341	1.344
6 Months	1.793	1.263	1.288	1.260	1.270	1.260	1.265
3 Months	1.767	0.819	0.825	0.815	0.823	0.816	0.821
1 Month	1.389	0.897	0.882	0.915	0.886	0.910	0.890
1 Week	1.256	1.222	1.233	1.211	1.230	1.214	1.227
1 Day	1.932	0.006	0.044	0.036	0.033	0.025	0.022
				Philippines Composite Price			
1 Year	2.252	1.716	1.719	1.719	1.719	1.718	1.720
9 Months	2.274	1.720	1.723	1.721	1.723	1.722	1.724
6 Months	2.426	1.913	1.914	1.913	1.914	1.913	1.915
3 Months	3.052	2.484	2.485	2.485	2.485	2.484	2.486
1 Month	4.290	3.814	3.810	3.815	3.813	3.812	3.813
1 Week	2.090	1.605	1.611	1.624	1.625	1.609	1.636
1 Day	3.127	1.605	0.136	0.201	0.202	0.129	0.238
				Strait Times Index			
1 Year	2.062	1.431	1.436	1.430	1.433	1.432	1.434
9 Months	2.035	1.425	1.430	1.423	1.426	1.426	1.428
6 Months	1.955	1.282	1.285	1.282	1.284	1.282	1.284
3 Months	2.040	1.341	1.285	1.340	1.344	1.342	1.345
1 Month	1.828	1.351	1.350	1.356	1.356	1.351	1.353
1 Week	2.172	2.174	2.171	2.188	2.189	2.173	2.181
1 Day	1.598	0.255	0.316	0.352	0.401	0.256	0.367
				Stock Exchange of Thai			
1 Year	2.135	1.677	1.677	1.678	1.677	1.679	1.677
9 Months	2.115	1.725	1.725	1.726	1.725	1.727	1.725
6 Months	1.981	1.565	1.559	1.569	1.560	1.568	1.561
3 Months	2.361	1.799	1.799	1.800	1.795	1.802	1.796
1 Month	2.421	2.184	2.161	2.192	2.167	2.197	2.169
1 Week	2.105	1.767	1.726	1.718	1.735	1.789	1.740
1 Day	2.297	0.036	0.089	0.127	0.155	0.013	0.074

Note: ARG, LSTARG, ESTARG stand for AR-GARCH, LSTAR-GARCH and ESTAR-GARCH models respectively.

Table 4
Ranking of Forecasting Models by Forecast Horizon

Countries	**RMSE**						
	RW	AR	ARG	ESTAR	ESTARG	LSTAR	LSTARG
				1 Year			
Indonesia	7	1	2	6	3	5	3
Malaysia	7	3	6	1	5	1	4
Philippines	7	1	3	3	3	2	6
Singapore	7	2	6	1	4	3	5
Thailand	7	1	1	5	1	6	1
Average	7.0	1.6	3.6	3.2	3.2	3.4	3.8
				9 Months			
Indonesia	7	1	1	5	3	5	3
Malaysia	7	3	6	1	4	1	3
Philippines	7	1	4	2	4	3	6
Singapore	7	2	6	1	3	3	5
Thailand	7	1	1	5	1	6	1
Average	7.0	1.6	3.6	2.8	3.0	3.6	3.6
				6 Months			
Indonesia	7	2	1	5	3	5	3
Malaysia	7	3	6	1	5	1	4
Philippines	7	1	4	1	4	1	6
Singapore	7	1	6	1	4	1	4
Thailand	7	3	6	6	1	4	2
Average	7.0	2.0	4.6	2.8	3.4	2.4	3.8
				3 Months			
Indonesia	7	5	6	1	3	1	3
Malaysia	7	3	6	1	5	2	4
Philippines	7	1	3	3	3	1	6
Singapore	7	3	1	2	5	4	6
Thailand	7	3	3	5	1	6	2
Average	7.0	3.0	3.8	2.4	3.4	2.8	4.2
				1 Month			
Indonesia	7	1	2	5	3	5	3
Malaysia	7	6	1	4	2	3	5
Philippines	7	5	1	6	3	2	3
Singapore	7	2	1	5	5	2	4
Thailand	7	5	1	4	2	6	3
Average	7.0	3.8	1.2	4.8	3.0	3.6	3.6
				1 Week			
Indonesia	7	1	1	1	1	1	1
Malaysia	7	3	6	1	5	2	4
Philippines	7	1	3	4	5	2	6
Singapore	2	4	1	6	7	3	5
Thailand	7	5	2	1	3	6	4
Average	6.0	2.8	2.6	2.6	4.2	2.8	4.0
				1 Day			
Indonesia	7	5	5	1	1	1	1
Malaysia	7	1	6	5	4	3	2
Philippines	7	6	2	3	4	1	5
Singapore	7	1	3	4	6	2	5
Thailand	7	2	4	5	6	1	3
Average	7.0	3.0	4.0	3.6	4.2	1.6	3.2

Notes: ARG, LSTARG, ESTARG stand for AR-GARCH, LSTAR-GARCH and ESTAR-GARCH models respectively.
For each forecast horizon, the ranking is done based on RMSE of each forecasting model.

Normal Errors versus GARCH Errors

On average, models with the assumption of GARCH errors do not out-performed models with normality assumption. Taking the 3-month forecast horizon for illustration, we notice that AR (1) – GARCH (1, 1) predicts better than AR (1) model in terms of average ranking. Meanwhile, ESTAR (1) – GARCH (1, 1) also give better forecasts than ESTAR (1, 1) model ranked second, on average. As for the LSTAR models, LSTAR (1) – GARCH (1, 1) model is superior to LSTAR (1) model as well. It is unknown whether the use of other GARCH variants such as Exponential GARCH (Nelson, 1991), Threshold GARCH models (Zakoin, 1990; Glosten *et al*., 1993) and Fractionally Integrated GARCH (Baille *et al*., 1996) will bring about improvement in terms of forecast performance.

ESTAR versus LSTAR

ESTAR (1) model has out-predicted LSTAR (1) model for all forecast horizon with the exception of 6-month and 1-week horizons, whereas ESTAR (1) – GARCH (1, 1) model has out-predicted LSTAR (1) – LSTAR (1) – GARCH (1, 1) model for all forecasts horizon excluding the 1-week and 1-day horizons. Thus, based on forecasting performance, the ESTAR specifications are in generally more appropriate than the LSTAR specifications in characterizing the behaviour of ASEAN-5 daily stock returns. This indicates that the ASEAN-5 stock market adjusts symmetrical towards over-valuation and under-valuation of daily stock returns[6].

V. CONCLUSIONS

Most previous studies on stock markets are based on fundamental analysis such as Efficient Market Hypothesis (EMH), Arbitrage Pricing Theory (APT) and Capital Asset Pricing Model (CAPM). The technical analysis has not received much attention for pure academic purposes. This study is therefore conducted to fill in this literature gap. Another motivation of this study is that stock prices were long believed to follow a geometric random walk with uncorrelated innovations. The unpredictable and random behaviour of stock market continue to be scrutinized by researchers. However, if time series model is capable of generating future asset prices or returns movements with acceptable accuracy, it would mean that the series is not unpredictable at all and the random walk hypothesis could be rejected. Thus, this study examines the forecastability of ASEAN-5 stock market returns, utilizing linear and non-linear time series models.

Besides utilizing models based on normality assumption, time series models with GARCH errors are also considered in this study to encounter for the heteroscedasticity problem, which is normally reported in financial time series. Based on formal econometrics tests, this study shows that the behaviour of these returns do not follow random walk movement. Results of this study also reveal that all the estimated time series models, both linear and non-linear, have smaller out-of-sample forecast errors than the random walk model. The major conclusion drawn from these two findings is that returns of ASEAN-5 stock markets do not follow random walk movement and are forecastable. Thus, this study can be taken as providing justification for the work of technical analysts.

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[6] ESTAR specification is deemed suitable for financial series that processes symmetrical adjustment mechanism, whereas LSTAR specification is best for those with asymmetrical adjustment mechanism. (Baum *et al*., 2001)

REFERENCES

Baum, C.F., Barkoulas, J.T. and Caglayan, M. (2001) Nonlinear adjustment to Purcahsing Power Parity in the Post-Bretton Woods era. *Journal of International Money and Finance*, 20: 379-399.

Bollerslev, T. (1986) Generalised Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics,* 51, 307–327.

Baillie, R. T., Bollerslev, T., and H. O. A., Mikkelsen (1996). Fractionally Integrated Generalised Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 74, 3 - 30.

Brock, W.A., Lakonishok, J. and LeBaron, B. (1992) Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, 47, 1731-1764.

Brockwell, P. J. and Davis, R. A. (1996) *Introduction to Time Series Forecasting*. New York: Springer-Verlag.

Clyde, W.C. and Osler, C.L. (1997) Charting: chaos theory in disguise? *Journal of Futures Markets*, 17, 489-514.

Cryer, J. D. (1990) *Time series analysis*. Boston: Duxbury Press.

Dockery, E. and Kavussanos, M.G. (1996) Testing the efficient market hypothesis using panel data, with application to the Athens stock market. *Applied Economics Letters*, 3, 121-123.

Engle, R. F. (1982) Autoregressive Conditional Heteroscedasticity, with estimation of the variance of United Kingdom inflation. *Econometrica*, 50, 987–1007.

Fama, E.F. (1976) *Foundations of Finance*. New York: Basic Books.

Fama, E.F. and French, K. (1988) Permanent and temporary components of stock prices. *Journal of Political Economy*, 96, 246-273.

Glosten, L.R., R. Jagannathan, and D. Runkle (1993) On the relation between the expected value and the volatility of the normal excess return on stocks. Journal of Finance, 48, 1779–1801.

Harvey, A.C. (1993) *Time Series Models.* 2nd edition. Great Britain: Harvester Wheatsheaf.

Lo, A.W. and MacKinlay, A.C. (1988) Stock market prices do not follow random walk: evidence from a simple specification test. *Review of Financial Studies*, 1, 41-66.

Nelson, Daniel B. (1991) Conditional Heteroskedasticity in asset returns: A new approach. Econometrica, 59, 347–370.

Lundbergh, S. and Teräsvirta, T. (1998) Modelling economic high-frequency time series with STAR-STGARCH models, Working Paper, Department of Economic Statistics, Stockholm, Sweden.

Pruitt, S.W. and White, R.E. (1988) The CRISMA trading system: who says technical analysis can't beat the market? *Journal of Portfolio Management*, 14, 55-58.

Pruitt, S.W. and White, R.E. (1989) Exchange-traded options and CRISMA trading. *Journal of Portfolio Management*, 15, 55-56.

Six, J. M. (1989) Economics and exchange rate forecasts. In C. Dunis and M. Feeny (eds.) *Exchange Rate Forecasting*, pp. 1 – 17. England: Woodhead-Faulkner.

Taylor, S. J. (1986) *Modelling Financial Time Series*. New York: John Wiley and Sons Ltd.

Taylor, M.P. and Allen, H. (1992) The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance*, 11, 304-314.

Terasvirta, T. (1994) Specification, estimation, and evaluation of Smooth Transition Autoregressive Models. *Journal of the American Statistical Association*, 89, 208-218.

Terasvirta, T. and Anderson, H. M. (1993) Characterizing nonlinearities in business cycles using Smooth Transition Autoregressive Models. In M.H. Pesaran and S.M. Potter (eds.) *Nonlinear dynamics, chaos and econometrics*, pp111-128. New York: John Wiley & Sons.

Tong, H. and Lim, K. S. (1980) Threshold Autoregressive, limit cycles and cyclical data. *Journal of Royal Statistical Society*, 42, 245-292.

Yokum, J.T. and Armstrong, J.S. (1995) Beyond accuracy: comparison of criteria used to select forecasting methods. *International Journal of Forecasting*, 11, 591-597.

Zakoian, J.M. (1990) "Threshold Heteroskedastic Models," manuscript, CREST, INSEE, Paris.

Zhu, Z. (1998) The random walk of stock prices: evidence from a panel of G-7 countries. *Applied Economics Letters*, 5, 411-413.