Int. Journal of Economics and Management 12 (S2): 731-745 (2018)

IJEM
International Journal of Economics and Management
Journal homepage: http://www.ijem.upm.edu.my

Volatility Forecasting of Real Estate Stock in Malaysia with Smooth Transition Exponential Smoothing

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ABSTRACT

In financial market, volatility forecast has been taking the deliberation of the academics and practitioners over the past decades in different areas of study. Malaysian real estate market has been in the long-run appreciation during years 2000-2013. A reliable volatility forecast in real estate stock market (sector) may provide important information for the central bankers, policymakers, investors, developers and public in decision making process (on real estate). Therefore, this research is to study the volatility forecasting performance of various forecasting models for the Malaysian real estate stocks. Daily returns of 33 Malaysian real estate stocks are used in this study. The forecasting models are ad-hoc methods, generalized autoregressive conditional heteroscedasticity (GARCH) models, and the newly proposed Smooth Transition Exponential Smoothing (STES) methods. Using Mean Absolute Error (MAE) as the evaluation criterion, the newly proposed STES models is found to be the most accurate forecasting model among the comparison models.

JEL Classification: G10, M20

Keywords: Real estate; volatility forecasting; exponential smoothing; smooth transition

Article history:
Received: 18 June 2018
Accepted: 21 November 2018

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INTRODUCTION

The real estate bubble and economic crisis

Real estate market stability is one of the pillars that could cause the economic crisis. The deterioration of the U.S real estate market has significant impact on the U.S. economy crisis 2008. It spreads to the financial market with the sub-prime mortgage market crisis which began in August 2007. This crisis has affected other sectors in U.S. and ultimately, ignited the Global Financial Crisis. This crisis clearly illustrates that, the sharp increase in the housing prices can lead to the "over-heating" of the economy, and vice versa (Leamer, 2007 qtd in (Crowe et al., 2013)).

The "real estate bubble" is a threat to the society if it burst as it would affect the national economy (The danger down the road of real estate boom). Cost of living may increase due to higher real estate price and rental. The welfare consequences have been mentioned in some studies (Glaeser, Gyourko and Saiz, 2008; Bianconi and Yoshino, 2012; Ott, 2016; Christensen, 2017). To prevent the collapse of the real estate market, preventive policy action has been urged to be introduced (Coleman IV, LaCour-Little and Vandell, 2008). One of the solutions is volatility forecasting. The risk of the European real estate stock markets is interdependent (Liow, 2013). There is integration of the world real estate markets. The recent global financial crisis is a glaring testimony to this. Misprice of the real estate investment will have negative impact to other sectors in the economy and the negative impact will spill over internationally (Hatemi-j, Roca and Al-shayeb, 2014). Besides, the risk of the European real estate stock markets is interdependent (Liow, 2013). The real estate stock market risk is globally integrated, therefore, real estate volatility forecasts is important and could become one of the good indicator in minimize the volatility (risk) in the real estate market of a country.

Volatility forecasting methods performance performs differently in different type of sectors or datasets. Many researches have been conducted on volatility forecasting models, such as Choo and Ahmad, Muhammad Idrees, 1999; Crawford and Fratantoni, 2003; Devaney, 2001; R. Engle, 2001; Miles, 2008; Zhou, 2013. However, none of the volatility forecast model provides best performance in all the data (WeiChong Choo and Ahmad, Muhammad Idrees, 1999; Devaney, 2001; Engle, 2001; Crawford and Fratantoni, 2003; Miles, 2008; Zhou, 2013). For robustness and accuracy short-term volatility forecasting of Malaysian real estate stock market, more empirical evidence focusing on Malaysian real estate stock market volatility forecast not only can fortify the volatility (risk) knowledge on the Malaysian real estate stock market, but also the developing countries.

Considering the increasing contribution of developing countries to the world economy over time our study is to analyse the volatility (risk) forecasting performance of ad-hoc methods, generalized autoregressive conditional heteroscedasticity (GARCH) models, Integrated GARCH (IGARCH), Exponential GARCH (EGARCH), GJR-GARCH (GJR) and newly purposed Smooth Transition Exponential Smoothing (STES) method in Malaysian property (real estate) stock market.

In the next section, we will review the literature on the circumstances of real estate bubble and volatility forecasts. The third section illustrates the research methodology as GARCH models and newly purposed STES method by James (2004). The fourth section illustrates the result and discussion. The final section provides a summary and conclusion.

REVIEW OF LITERATURE

Importance of volatility forecasting methods

The volatility forecasting is a crucial duty and it has been taken the deliberation of academics and practitioners over the past decades in the financial markets. The concern of volatility forecasting in stock market investment, security valuation, risk management, and monetary policymaking is reflected by these extensive researches (WeiChong Choo and Ahmad, Muhammad Idrees, 1999; Engle, 2001; Lee and Pai, 2010; Engle and Sokalska, 2012; Heaney and Srinanthakumar, 2012). Volatility forecasting study has received considerable attention from the policymakers and financial market players because it can be used as a tool to forecast the risk. Secondly, the volatility in the stock, bond, and foreign exchange markets, raising important public policy issues, affect the stability of the financial markets and have impacts on the national economy.

Thirdly, from a theoretical perspective, the volatility acts as an important part of the valuation of the derivative securities. Finally, for the aims of forecasting return series, forecast confidence intervals may be time-varying, and a more accurate interval can be achieved by modelling volatility of returns(Gupta, Jurgilas and Kabundi, 2010). Yet, volatility forecast is not an easy task.

Lack of empirical evidences in developing country

There are only a few attempts that have been made statistically to evaluate risk and return relationship of the real estate stock market in developing countries. The studies that have been conducted till to-date tend to focus more on the developed countries data such as US market and European market (Devaney, 2001; Crawford and Fratantoni, 2003; Rapach and Strauss, 2007, 2009; Miles, 2008; Das, Gupta and Kabundi, 2009; Chang, 2010; Ken, 2010; Zhou, 2013; Gupta, 2013; Sing and Tan, 2013; vasilios Plakandaras, Rangan Gupta, Periklis Gogas, 2014). Many volatility forecasting models have been adopted in forecasting the real estate market volatility. However, there are mixed evidences on the best performing volatility forecasting model from previous studies especially in real estate stocks. Apart from this, it is especially crucial where there is rare literature focusing on the real estate stock market volatility of developing countries data (China, Malaysia, India and more) where these countries may have different implications as compared to developed countries (US, UK, European countries, Singapore and more). The economic contribution of developing countries to the world economy has significantly increased over the past 10 years. Besides, most of the studies have been done using the real estate indices instead of individual share prices. Moreover, literature focusing on individual real estate stocks (developer companies) volatility is infrequent. Predominantly the literature on either volatility or volatility forecasting of the Malaysian real estate stock market is rare. In other words, there is not enough knowledge on understanding the volatility (risk) forecasting of Malaysian real estate stock market. This is not a good sign for Malaysian real estate stock market nor the Malaysia economic (without risk consciousness).

MODELS

GARCH (1,1)

Consider a stock price is P_t, we are using log return, hence the rate of return at time t is $r_t = \frac{P_{t+1}}{P_t}$. The GARCH family models have been used in this non-stationary data. Using the maximum likelihood method, the GARCH family models enables the stock price return and the variance process to be estimated together. All the prediction errors from the model can be calculated in the function of the log-likelihood method. The function of the log-likelihood method is to compute the probability densities of the prediction error.

$$l = \sum_{t=1}^{n} \frac{1}{2}\left(-\ln(2\pi) - \ln(h_t) - \frac{\varepsilon_t^2}{h_t} \right)$$

The error term at time t can be defined as $\boldsymbol{\varepsilon_t = r_t - \mu}$ on the GARCH regression model for the series of $\boldsymbol{r_t}$. The uncertainty of stock returns can be indicated by the volatility of a stock. In the financial market, the volatility can be measured by the standard deviation, $\boldsymbol{\sigma}$ or variance $\boldsymbol{\sigma^2}$. The $\boldsymbol{\sigma}$ is the conditional standard deviation of return at the time t The variance at time t would be $\boldsymbol{\sigma_t^2 = \varepsilon_t^2 = h_t}$. The variance can be computed as follows:

$$\boldsymbol{\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(r_t - \mu)^2}$$

Where the $\boldsymbol{\mu}$ is the mean return. $\boldsymbol{\varepsilon_t}$ at time t often treated as the price or news "shock" during time t. The conditional variance $\boldsymbol{h_t}$ is :

$$\boldsymbol{h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}}$$

Where $\boldsymbol{\varepsilon_t = \sqrt{h_t}e_t}$, $\boldsymbol{e_t \sim N\ (0, 1)}$, p ≥ o, q> 0 and $\boldsymbol{\omega}$>0, $\boldsymbol{\alpha_i}$≥ 0, $\boldsymbol{\beta_j \geq 0}$ for non-negative GARCH process. To ensure the stationarity of GARCH process, the stationary condition of $\boldsymbol{\alpha + \beta < 1}$ should be held. GARCH model is symmetric in modeling volatility and the $\boldsymbol{\alpha}$ indicates the short-run persistency of shocks while $\boldsymbol{\beta}$indicates the long-run persistency. Overtime, the GARCH models have been modified to model the asymmetric feature of stock market volatility and among the models, GJR-GARCH and EGARCH have been used in this study.

GJR GARCH

The asymmetric GJR-GARCH model (GJR) is defined as:

$$\boldsymbol{\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\, \sigma_{t-j}^2 + \sum_{i=1}^{p} I_{t-i}\, \varepsilon_{t-i}^2}$$

Where:

$$\boldsymbol{I_{t-i} = \begin{cases} 1\ if\ \varepsilon_{t-i}^2 < 0 \\ 0\ if\ \varepsilon_{t-i}^2 \geq 0 \end{cases}}$$

EGARCH (1,1)

The exponential GARCH (EGARCH) may generally be specified as:

$$\boldsymbol{ln\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j ln\, \sigma_{t-j}^2}$$

EGARCH using the log of the variance in the modelling and $\boldsymbol{\beta_j}$ indicates the asymmetric effect of shocks on volatility and the positive value of the parameter implies the presence of leverage effect of the sample.

IGARCH

Integrated GARCH (IGARCH) model has applied both autoregressive and moving average structure to the variance, $\boldsymbol{\sigma^2}$. It can be denoted as:

$$\boldsymbol{h_t = \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}}$$

IGARCH constrained the sum of $\boldsymbol{\alpha_i + \beta_j = 1}$.

Ad hoc methods (forecasting approach)

The ad hoc forecasting approach we used in this study are random walk (RW), naïve forecast, simple 30 days moving average (MA30), exponential weighted moving average 0.06 (EWMA (0.06)), and optimized exponential smoothing model (EWMA).

Smooth transition exponential smoothing

One of the popular, simple and pragmatic approach for volatility forecasting is exponential smoothing. It is widely used in forecasting due to its robustness and accuracy for short-term forecasting. However, the changing of smoothing parameter overtime so that it can adapt to the latest characteristics of the time series have been argued by many researchers (Taylor, 2004b). Hence, STES method, using a logistic function of a user-specified variable as adaptive smoothing parameter α_t. The α_{t-1} will vary between 0 and 1, changed by adapts according to the changes in transition variable $V_{t-1,}$ was developed by James W. Taylor in 2004. The STES method is similar to the logistic function of exponential smooth transition GARCH model (ESTGARCH) model. The formula is formulated as follows:

$$\hat{\sigma}_t^2=\alpha_{t-1}\varepsilon_{t-1}^2+(1-\alpha_{t-1})\sigma_{t-1}^2$$

$$\text{Where } \alpha_{t-1}=\frac{\omega}{1+exp(\beta+\gamma V_{t-1})}$$

The ω, β and γ are constant parameters and V_{t-1} depends on γ<0 and ω>0 and vice versa. If γ < 0, α_{t-1} is a perpetually increasing function of V_{t-1}. whereby when V_{t-1} increases, the weight on α_{t-1} will decrease, and therefore the weight of σ_{t-1}^2 will increase. The α_{t-1} lie between 0 and 1 bounded by the logistic function. V_t becomes a perpetually increasing function if γ <0. Through the estimation of β and γ, this approach uses the historical data to regulate the adaptive smoothing parameter, α_t (Taylor, 2004a). Broadly, by applying logistic function in the smooth transition to exponential smoothing model, Smooth Transition Exponential Smoothing (STES) is the combination of smooth transition model and exponential smoothing model. Therefore, it can be recognized as smooth transition exponential (STES).

Five STES methods will be used in this empirical work where these models are rarely used for real estate (property) data, especially in Malaysia. Five different transition variables used in STES methods which are: ε_{t-1} (STES-E); $|\varepsilon_{t-1}|$ (STES-AE); ε_{t-1}^2 (STES-SE); $\varepsilon_{t-1}$and $|\varepsilon_{t-1}|$ together (STES EandAE); ε_{t-1} and ε_{t-1}^2 together (STES-ESE). The minimization equation below will be used to optimize the STES parameters:

$$Min\sum\left|\varepsilon_i^2-\hat{\sigma}_i^2\right|$$

One of the specialities about STES EandAE method is, it can provide a complex asymmetry forecast. According to the news impact curve (NIC), when small positive shocks, this model introduce slightly more volatility than small negative shocks but more volatility for large negative shocks than the large positive shock. STES method has been found better as compared with a variety of presence GARCH family models and fixed parameter exponential smoothing model (Taylor, 2004b).

RESEARCH METHODOLOGY

The samples we adopted in this study are thirty-three Malaysian real estate (property) companies individual stock price daily return (which is traded in Bursa Malaysia from 18 February 2009 to 16 October 2016 after global financial crisis (GFC)). Data were collected from Yahoo finance and datastream. We have split each series 2000 observations (N) into two groups, in-sample (1500 observations) and out-of-sample (500 observations) to simulated out-of-sample forecasting framework with total 66,000 observations. We focused on 1-step ahead forecasting volatility in daily log returns. Taylor (2004b) used nine years of weekly return of eight major stock markets indices in his study while our study used daily return (shorter return interval) of thirty-three real estate stock prices. With the growing of Artificial Intelligent (AI) and big data analysis, focused on one sector and shorter choice of return interval could provide more responsive insights or better volatility forecast accuracy (as proxy of one sector). Figure 1 presents the stock price of each company (not stationary). Stock price daily returns for each series were obtained in this study.

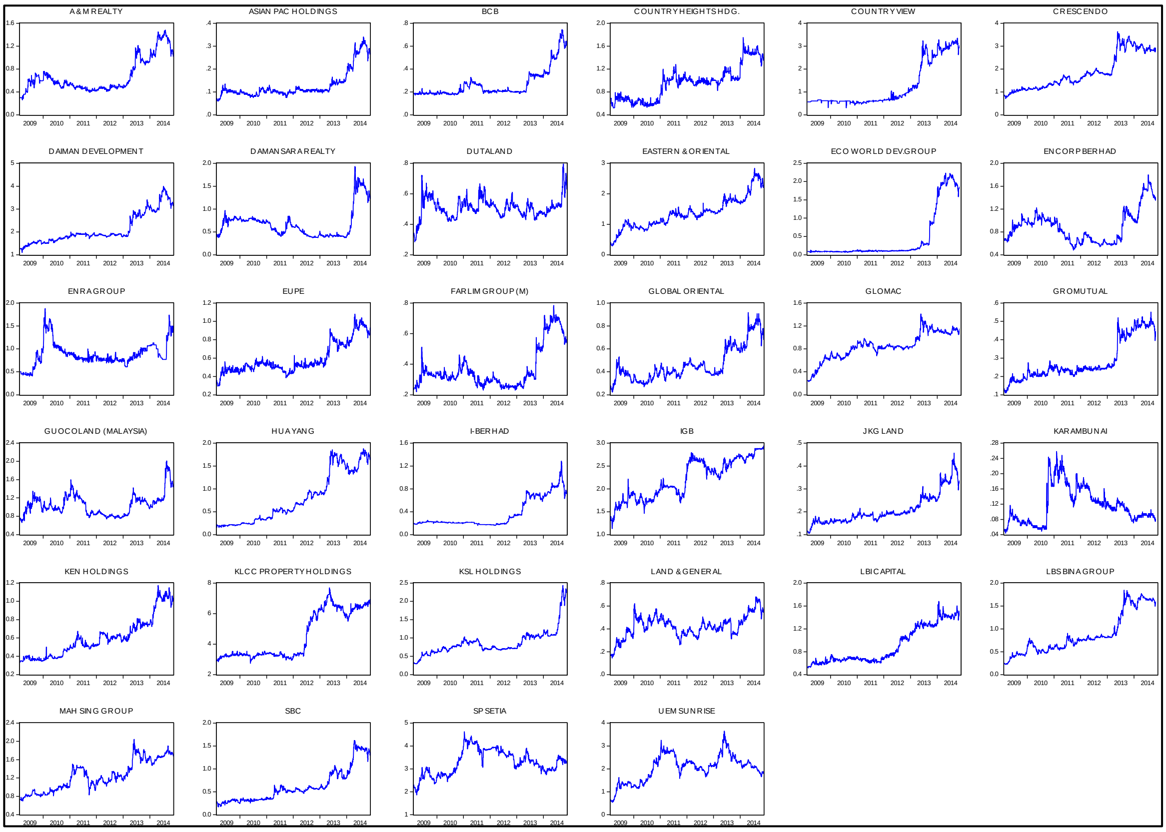

Figure 1 Real estate stock price

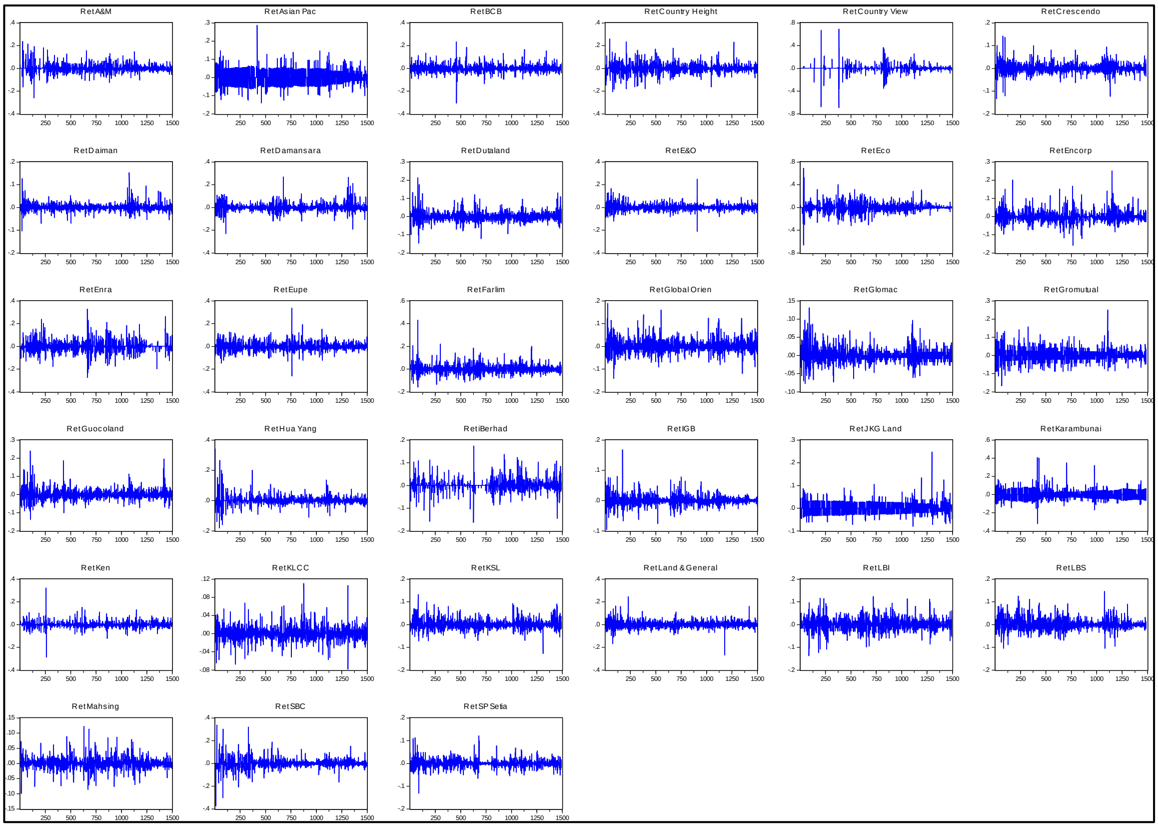

Figure 2 Real estate stock price daily return

Table 1 Summary statistic of daily stock return

Company Return	Mean (x 10^2)	n	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
RET_AM	0.000858	1500	0.2384	-0.2607	0.03291	0.8039	13.69
RET_ASIANP	0.000949	1500	0.2877	-0.1398	0.03970	0.3757	5.28
RET_BCB	0.000801	1500	0.2326	-0.3067	0.03013	0.2395	16.10
RET_COUNTRYH	0.000462	1500	0.2586	-0.2057	0.03705	0.3542	11.28
RET_COUNTRYV	0.001085	1500	0.6931	-0.6931	0.05634	-0.1205	68.33
RET_CRESCENDO	0.000797	1500	0.1427	-0.1335	0.01988	0.3388	11.82
RET_DAIMAN	0.000607	1500	0.1528	-0.1035	0.01572	1.5933	18.74
RET_DAMANSARA	0.000671	1500	0.2693	-0.2294	0.03347	0.8937	13.92
RET_DUTALAND	0.000432	1500	0.2132	-0.1466	0.02552	1.1226	12.55
RET_EandO	0.001129	1500	0.2496	-0.2095	0.02737	0.7880	12.84
RET_ECO	0.00201	1500	0.6931	-0.6614	0.06980	0.4035	20.93
RET_ENCORP	0.000462	1500	0.2513	-0.1591	0.02829	1.3661	13.76
RET_ENRA	0.000705	1500	0.3285	-0.2744	0.04383	0.6362	12.16
RET_EUPE	0.000603	1500	0.3365	-0.2616	0.03397	0.6459	14.21
RET_FARLIM	0.000559	1500	0.4290	-0.1591	0.03642	1.9607	20.16
RET_GLOBAL	0.000617	1500	0.1884	-0.1411	0.02806	0.7430	7.80
RET_GLOMAC	0.001002	1500	0.1315	-0.0776	0.01899	0.8625	8.23
RET_GROM	0.000765	1500	0.2498	-0.1671	0.03127	0.6152	8.50
RET_GUOCO	0.000467	1500	0.2403	-0.1361	0.02653	1.5485	14.79
RET_HUAYANG	0.001607	1500	0.3412	-0.1802	0.02728	2.3819	34.36
RET_IBERHAD	0.000916	1500	0.1738	-0.1632	0.02335	0.4054	14.71
RET_IGB	0.000492	1500	0.1679	-0.0961	0.01564	1.1127	16.35
RET_JKG	0.000691	1500	0.2474	-0.0800	0.02330	1.2374	13.07
RET_KEN	0.000765	1500	0.3230	-0.2877	0.02514	0.9016	36.12
RET_KLCC	0.000565	1500	0.1103	-0.0782	0.01449	0.6364	10.59
RET_KSL	0.001314	1500	0.1324	-0.1276	0.02000	0.7043	8.13
RET_LAND	0.000763	1500	0.2451	-0.2691	0.02996	0.4010	13.28
RET_LBI	0.000651	1500	0.1232	-0.1372	0.02409	0.1712	8.04
RET_LBS	0.001291	1500	0.1461	-0.1051	0.02352	0.7015	7.11
RET_MAHSING	0.000564	1500	0.1221	-0.0995	0.01792	0.3442	9.86
RET_SBC	0.001014	1500	0.3382	-0.3725	0.03821	0.3665	24.96
RET_SP_SETIA	0.000264	1500	0.1214	-0.1316	0.01686	0.5892	12.26
RET_UEM	0.000695	1500	0.1757	-0.1407	0.02386	0.8608	9.96

The characteristics of the daily stock return of each series are presented in Figure 2. Figure 2 shows the volatility clustering in the series (stock price return). In the in-sample observations, Table 1 shows that the skewness of the series is either negative or positive hence the series are non-stationary. Almost all the series are positive skew but only one series (Country View Berhad) is negative skew (positive skew means the mean return is higher than the median return and vice versa). Furthermore, among the series, this series (Country View Berhad) has the widest interval between maximum return (0.693147) and minimum return (-0.69315). However, it does not have the largest standard deviation but Ecoworld series (0.069799). Both Ecoworld and Country View series have highest and lowest return. They are among the highest volatility accompany with high standard deviation 0.06980 and 0.5634 respectively. The lowest volatility belongs to KLCC Berhad (0.01449) within this sample period.

From Table 1, all the kurtosis of the series is leptokurtic. Because all the series are skew, it is suggested that non-stationary model such as GARCH models should be used in modelling the in-sample return.

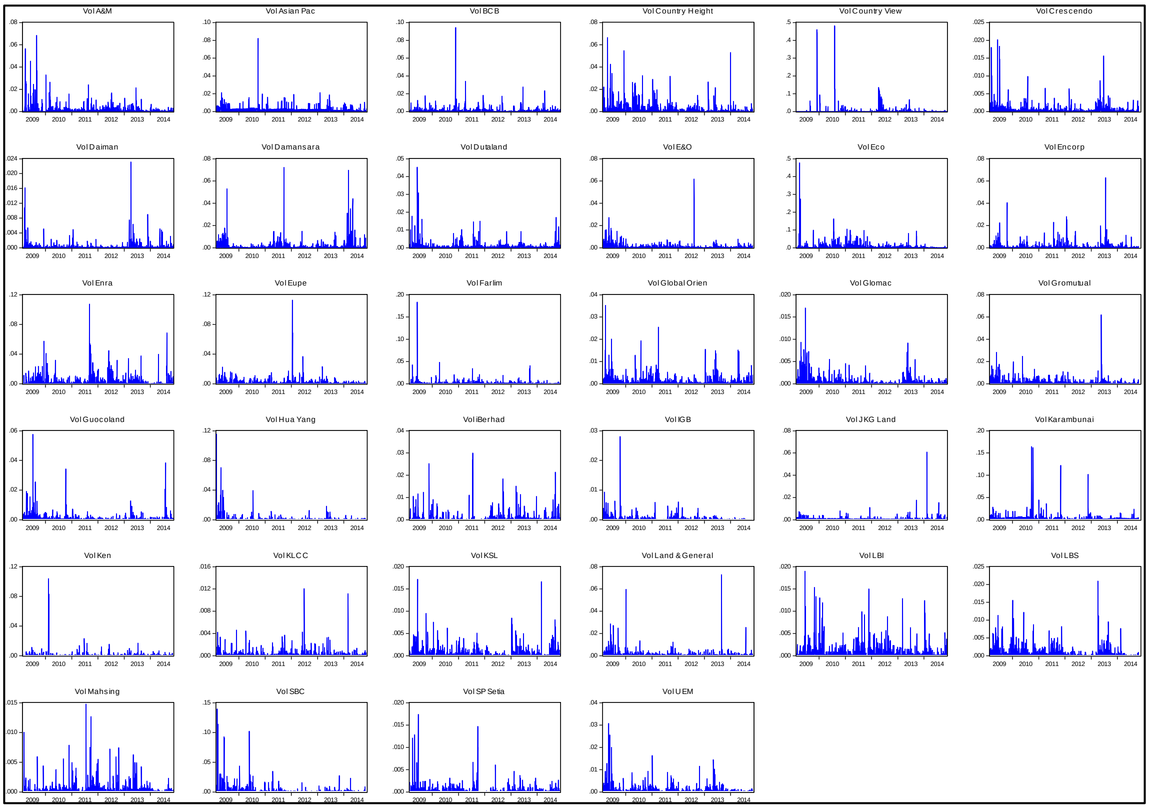

Figure 3 Individual stock return volatility

The volatility patterns of the series are different. The characteristic of the stock return volatility (risk) of each series is presented in the Figure. 3. The daily residual of the series is obtained by deducted the mean return of each series. The squared residual represents the daily volatility of the series. From the observations in Figure.3, we may notice that, not all series has high volatility. For example, JKG land, Farlim, and Hua Yang are found to be less volatile during the study period. Except in certain study period, as compared to LBS, LBI, Mahsing, and country height, these series are far more volatile. This has implied that, further investigation needs to be carried out to find out more, which volatility forecasting model can consistently provide good volatility forecasting accuracy for each series (management science is important). This can assist in the investment decision making (risk management) in Malaysian real estate (property) stock market.

The goodness of fit of each model in the in-sample observation will be evaluated by loglikelihood (Log L), Akaike's information criterion (AIC) and Schwarz's Bayesian information criterion (SBC). The goodness of fit explains how well a regression model can fit well with true observations (lowest error between the estimated value and observed value in the model). Ranking is given to GARCH family models based on evaluation criteria for each series. We calculated the average ranking of each method and the lowest average ranking of the model is the best volatility forecasting model.

Newly proposed volatility forecasting method Adaptive STES method (Taylor, 2004b), will be used to compare against other volatility forecasting models such as GARCH family models. In the volatility forecasting, predicted values of the model will then be used in the out-of-sample comparison. This is to evaluate its volatility forecast ability (Malaysian listed real estate stock price return volatility) as compared to other volatility forecasting models.

The out-of-sample volatility forecasting performance of each model will be evaluated by popular evaluation criteria means absolute error (MAE) whereby the lower the value, the better the forecast ability of the model is. All the methods will be ranked based on MAE and the average ranking of each method is presented by Table 7. The MAE is given as,

$$\text{MAE} = \frac{1}{n}\sum_{j=1}^{n}\left|h_t - \sigma_t^2\right|$$

Besides, we calculated the Theil-U (Theil-U measure calculated as the ratio of the MAE for that method of each series to the MAE for the GJR model) for each series which has been suggested by Poon and

Granger (2002) (qtd. In (Taylor, 2004b)). Total MAE of each models and Theil-U of volatility forecasting models for all series will be computed for volatility forecast performance evaluation. The mean Theil-U value will be calculated. This Theil-U value indicates the relatively (ratio) MAE of each model to the MAE of GJR model. The Theil-U value of each model will be ranked afterwards. The lower the average ranking, the better the forecast ability of that model.

RESULTS AND DISCUSSION

Table 2 shows that the GARCH effect existed and persists in these series. GARCH parameter estimates are found significant in all the series. Thus, we can affirm that, there is an existence of GARCH effect in the series. In another word, the constant variance model can be rejected. Besides, the conditional volatility is persistent in the models. These are indicated by adding up the beta and alfa value ($\beta+\alpha = 1$) of each GARCH model with less than and near to 1.

Table 2 Empirical GARCH Model

		GARCH			
Company	Variable	ω (x10^{-5})	α	β	$\beta+\alpha$
AandM Realty	Coefficient	6.180	0.064	0.880	0.945
	Std. Error	0.349	0.004	0.005	0.009
	Prob.	0.000	0.000	0.000	0.000
Asian Pac Holding	Coefficient	26.900	0.108	0.723	0.831
	Std. Error	4.220	0.020	0.037	0.058
	Prob.	0.000	0.000	0.000	0.000
BCB	Coefficient	13.000	0.195	0.678	0.873
	Std. Error	1.450	0.017	0.026	0.043
	Prob.	0.000	0.000	0.000	0.000
Country Height	Coefficient	4.290	0.039	0.930	0.969
	Std. Error	0.593	0.005	0.008	0.013
	Prob.	0.000	0.000	0.000	0.000
Country View	Coefficient	76.200	0.136	0.574	0.709
	Std. Error	4.130	0.014	0.023	0.037
	Prob.	0.000	0.000	0.000	0.000
Crescendo	Coefficient	0.788	0.069	0.913	0.982
	Std. Error	0.121	0.007	0.009	0.016
	Prob.	0.000	0.000	0.000	0.000
Daimen Development	Coefficient	1.680	0.167	0.785	0.952
	Std. Error	0.121	0.009	0.010	0.019
	Prob.	0.000	0.000	0.000	0.000
Damansara Realty	Coefficient	1.630	0.154	0.852	1.007
	Std. Error	0.189	0.009	0.008	0.017
	Prob.	0.000	0.000	0.000	0.000
Dutaland	Coefficient	0.910	0.081	0.907	0.988
	Std. Error	0.154	0.006	0.006	0.012
	Prob.	0.000	0.000	0.000	0.000
Eastern and Oriental	Coefficient	1.610	0.068	0.912	0.980
	Std. Error	0.291	0.009	0.010	0.019
	Prob.	0.000	0.000	0.000	0.000
Eco World	Coefficient	9.880	0.126	0.875	1.001
	Std. Error	0.647	0.005	0.004	0.009
	Prob.	0.000	0.000	0.000	0.000
Encorp Berhad	Coefficient	9.450	0.124	0.766	0.891
	Std. Error	0.918	0.012	0.021	0.033
	Prob.	0.000	0.000	0.000	0.000
Enra Group	Coefficient	8.730	0.070	0.887	0.957
	Std. Error	0.607	0.004	0.006	0.011
	Prob.	0.000	0.000	0.000	0.000

The goodness of fit statistic (in-sample performance) has been used to rank GARCH family models performance for each series. The results are presented in Table 3, 4 and 5. Overall, based on the average ranking evaluation, GARCH ranked number one (based on SBC) in the property indices. This result is consistent with the result of Choo et al. (1999) based on maximum Log likelihood (Log L). Yet, there are different results based on maximum Log likelihood (see Table 3) and AIC (see Table 4) which ranked GJR as number one in the in-sample goodness of fit evaluation. These results are contradicted with Choo et al. (1999) which suggested GARCH in the property indices. GJR model is not included in the Choo et al. (1999) study. GJR model gives more weight when yesterday observation is a negative return. This may indicate that most of the series (from the 33 series) has the characteristic of more volatile when yesterday observation (return) is a negative return. In average ranking performance based on the goodness of fit, the statistic has suggested GJR to be the best model followed by GARCH model, EGARCH and lastly IGARCH.

In the comparison of out-of-sample volatility forecasting performance among the forecasting models of the study period (500 out-of-sample observations). In the one step ahead volatility forecasting accuracy, when STES parameter optimized based on MAE and ranked by MAE, as presented in Table 6, the Theil-U ranking (Table 7), average ranking of each method, and total MAE ranking (the lesser the better) suggested STES-AE as the most accurate volatility forecasting model (among the forecasting models) in Malaysian real estate stock market. The result is encouraging because it is consistent with the study done by Taylor (2004) that the STES methods performed better than GARCH family models in volatility forecasting.

Fitting good in in-sample observation does not necessarily good in forecasting. In this study, volatility forecasting performance of GARCH model ranked at 11th and GJR ranked at 12th (we take middle rank) based on MAE (optimized by MAE) (refer Table 6) even if they were ranked best in in-sample goodness of fit. GARCH family models volatility forecasting performance are poorer in this study period as compared with STES method (STES-AE). Therefore, we conclude that STES method (STES-AE) volatility forecasting performance consistently outperformed other volatility forecasting models in this study period.

Table 3 In-sample performance and ranking of the models across 33 listed companies based on Log likelihood

	Log Likelihood				Ranking			
Company	GARCH	IGARCH	EGARCH	GJR	GARCH	IGARCH	EGARCH	GJR
AandM Realty	3073.5	3047.9	3040.8	3075.7	2	3	4	1
Asian Pac Holding	2736.8	2736.4	2730.5	2737.2	2	3	4	1
BCB	3238.9	3139.3	3251.7	3248.5	3	4	1	2
Country Height	2866.0	2846.1	2844.5	2866.0	2	3	4	1
Country View	2462.2	1180.6	2443.2	2282.8	1	4	2	3
Crescendo	3888.4	3863.2	3872.7	3888.6	2	4	3	1
Daimen Develop	4272.9	4177.9	4266.7	4275.2	2	4	3	1
Damansara Realty	3262.9	3222.1	3271.5	3269.6	3	4	1	2
Dutaland	3605.1	3584.1	3627.7	3625.9	3	4	1	2
Eastern and Oriental	3413.9	3381.3	3427.9	3420.4	3	4	1	2
Eco World	2080.2	1995.3	2041.5	2089.2	2	4	3	1
Encorp Berhad	3306.0	3245.8	3308.1	3309.9	3	4	2	1
Enra Group	2671.6	2495.7	2648.6	2671.8	2	4	3	1
Eupe	3010.2	2997.1	3005.6	3013.5	2	4	3	1
Farlim Group	3011.1	2931.2	2984.5	3011.1	2	4	3	1
Global Oriental	3354.8	3286.8	3356.7	3355.6	3	4	1	2
Glomac	4063.1	4042.7	4054.3	4063.7	2	4	3	1
Gromutual	3170.1	3156.8	3181.6	3183.6	3	4	2	1
Guocoland	3474.0	3416.1	3461.7	3476.3	2	4	3	1
Hua Yang	3570.4	3525.4	3533.3	3571.6	2	4	3	1
I Berhad	3629.5	3506.1	3641.4	3638.4	3	4	1	2
IGB	4419.3	4391.2	4426.1	4419.9	3	4	1	2
JKG Land	3532.2	3501.6	3536.5	3532.4	3	4	1	2
Kenholding	3545.8	3435.7	3536.4	3545.8	2	4	3	1
KLCC	4272.6	4213.8	4275.2	4273.4	3	4	1	2
KSL Holding	3823.9	3764.0	3832.3	3828.5	3	4	1	2
Land and General	3211.2	3153.6	3204.7	3211.3	2	4	3	1
LBI	3555.7	3505.6	3550.2	3556.2	2	4	3	1
LBS	3724.6	3704.6	3745.2	3728.4	3	4	1	2
Mahsing	4017.7	3942.9	4025.6	4018.2	3	4	1	2
SBC	3000.1	2981.2	2962.9	3000.9	2	3	4	1
SP Setia	4142.7	4095.7	4168.7	4150.5	3	4	1	2
UEM	3640.7	3623.4	3641.8	3642.1	3	4	2	1
Mean					3	4	2	**1**

Table 4 In-sample performance and ranking of the models across 33 listed companies based on AIC

	AIC				Ranking			
Company	GARCH	IGARCH	EGARCH	GJR	GARCH	IGARCH	EGARCH	GJR
AandM Realty	-4.094	-4.063	-4.049	-4.096	2	3	4	1
Asian Pac Holding	-3.645	-3.647	-3.635	-3.644	2	1	4	3
BCB	-4.315	-4.184	-4.330	-4.326	3	4	1	2
Country Height	-3.817	-3.793	-3.787	-3.816	1	3	4	2
Country View	-3.279	-1.573	-3.252	-3.038	1	1	1	1
Crescendo	-5.181	-5.150	-5.158	-5.179	1	4	3	2
Daimen Develop	-5.693	-5.569	-5.684	-5.695	2	4	3	1
Damansara Realty	-4.347	-4.295	-4.357	-4.354	3	4	1	2
Dutaland	-4.803	-4.777	-4.832	-4.829	3	4	1	2
Eastern and Oriental	-4.548	-4.507	-4.565	-4.555	3	4	1	2
Eco World	-2.770	-2.659	-2.717	-2.780	2	4	3	1
Encorp Berhad	-4.404	-4.326	-4.405	-4.408	3	4	2	1
Enra Group	-3.558	-3.326	-3.526	-3.557	1	4	3	2
Eupe	-4.010	-3.995	-4.002	-4.013	2	4	3	1
Farlim Group	-4.011	-3.907	-3.974	-4.010	1	4	3	2
Global Oriental	-4.469	-4.381	-4.470	-4.469	2	4	1	3
Glomac	-5.413	-5.389	-5.400	-5.413	1	4	3	2
Gromutual	-4.223	-4.208	-4.237	-4.239	3	4	2	1
Guocoland	-4.628	-4.553	-4.610	-4.630	2	4	3	1
Hua Yang	-4.757	-4.699	-4.706	-4.757	2	4	3	1
I Berhad	-4.835	-4.673	-4.850	-4.846	3	4	1	2
IGB	-5.888	-5.854	-5.896	-5.888	2	4	1	3
JKG Land	-4.706	-4.667	-4.710	-4.704	2	4	1	3
Kenholding	-4.724	-4.580	-4.710	-4.722	1	4	3	2
KLCC	-5.693	-5.617	-5.695	-5.693	2	4	1	3
KSL Holding	-5.095	-5.017	-5.104	-5.099	3	4	1	2
Land and General	-4.278	-4.204	-4.268	-4.276	1	4	3	2
LBI	-4.737	-4.673	-4.728	-4.736	1	4	3	2
LBS	-4.962	-4.938	-4.988	-4.966	3	4	1	2
Mahsing	-5.353	-5.256	-5.362	-5.352	2	4	1	3
SBC	-3.996	-3.974	-3.945	-3.996	1	3	4	2
SP Setia	-5.520	-5.460	-5.553	-5.529	3	4	1	2
UEM	-4.840	-4.830	-4.850	-4.851	3	4	2	1
Mean					2	4	3	**1**

Table 5 In-sample performance and ranking of the models across 33 listed companies based on SBC

	SBC				Ranking			
Company	GARCH	IGARCH	EGARCH	GJR	GARCH	IGARCH	EGARCH	GJR
AandM Realty	-4.083	-4.059	-4.035	-4.081	1	2	2	1
Asian Pac Holding	-3.634	-3.644	-3.621	-3.630	2	1	4	3
BCB	-4.304	-4.181	-4.316	-4.312	3	4	1	2
Country Height	-3.807	-3.790	-3.773	-3.802	1	3	4	2
Country View	-3.268	-1.569	-3.238	-3.024	1	4	2	3
Crescendo	-5.170	-5.146	-5.144	-5.165	1	3	4	2
Daimen Develop	-5.683	-5.566	-5.669	-5.681	1	4	3	2
Damansara Realty	-4.336	-4.291	-4.343	-4.340	3	4	1	2
Dutaland	-4.792	-4.774	-4.817	-4.815	3	4	1	2
Eastern and Oriental	-4.537	-4.503	-4.551	-4.541	3	4	1	2
Eco World	-2.759	-2.656	-2.703	-2.766	2	4	3	1
Encorp Berhad	-4.393	-4.323	-4.391	-4.394	2	4	3	1
Enra Group	-3.547	-3.323	-3.512	-3.543	1	4	3	2
Eupe	-3.999	-3.991	-3.988	-3.998	1	3	4	2
Farlim Group	-4.000	-3.903	-3.960	-3.995	1	4	3	2
Global Oriental	-4.458	-4.377	-4.456	-4.455	1	4	2	3
Glomac	-5.403	-5.385	-5.386	-5.399	1	4	3	2
Gromutual	-4.212	-4.204	-4.223	-4.225	3	4	2	1
Guocoland	-4.617	-4.550	-4.596	-4.616	1	4	3	2
Hua Yang	-4.746	-4.696	-4.692	-4.743	1	3	4	2
I Berhad	-4.825	-4.670	-4.836	-4.832	3	4	1	2
IGB	-5.878	-5.850	-5.882	-5.874	2	4	1	3
JKG Land	-4.695	-4.664	-4.696	-4.690	2	4	1	3
Kenholding	-4.713	-4.576	-4.696	-4.708	1	4	3	2
KLCC	-5.682	-5.613	-5.681	-5.678	1	4	2	3
KSL Holding	-5.084	-5.014	-5.090	-5.085	3	4	1	2
Land and General	-4.267	-4.200	-4.253	-4.262	1	4	3	2
LBI	-4.726	-4.669	-4.714	-4.722	1	4	3	2
LBS	-4.951	-4.935	-4.974	-4.952	3	4	1	2
Mahsing	-5.342	-5.252	-5.348	-5.338	2	4	1	3
SBC	-3.985	-3.970	-3.931	-3.982	1	3	4	2
SP Setia	-5.509	-5.456	-5.539	-5.515	3	4	1	2
UEM	-4.840	-4.826	-4.836	-4.837	1	4	3	2
Mean					**1**	4	3	2

Table 6 MAE($x10^6$)(mean Theil-U) for 500 out of sample variance forecast (33 companies) and models ranking (optimized by MAE)

	RW	naïve	MA30	EWMA (0.06)	EWMA- Opt	GARCH	GJR	IGARCH	EGARCH
AandM	638.1	960.3	509.9	504.4	507.7	699.7	656.6	499.4	856.1
Asian Pac	802.9	1322.13	696.4	678.2	712.4	1016.1	998.3	696.4	1168.7
BCB	1013	1045	892.5	875.6	875.1	935.8	939.3	875.1	930.2
Country H	1171	1364	1089	1082	1082	1197	1197	1062	1281
Country V	685.3	2882.4	599.7	597.3	658.3	1746.8	4067.7	592.7	2547.9
Crescendo	344.3	398.5	292.2	289.9	292.2	311.8	314.3	291.5	319.3
Daiman	361.3	331.8	312.5	312.8	312.4	328.3	333.2	313	327.2
Dsr Realty	1862	1477	1637	1598	1614	1718	1811	1601	1980
Dutaland	532	637.4	483.4	472.1	462.2	481.3	474.4	469.4	468.4
EandO	465.5	655.8	396.7	395.4	390.6	447.4	433.7	399.2	436
Ecoworld	480.9	4536.9	404.1	402	446.9	983.6	811.4	402.4	1384.1
Encorp	1317	1190	1220	1216	1226	1230	1226	1210	1200
Enra Group	1683	2148	1657	1629	1615	1805	1808	1718	1919
Eupe	1106	1224	942.4	935	936.7	1009	1066	926.3	1096
Farlim	662.9	1206.9	578.3	571	570.5	723	723.1	570.6	748.5
Global O	728.5	779.1	596.5	593.5	595	645	636.1	594.3	622.3
Glomac	413.5	415.1	356.6	355.7	347.2	356.6	356	357.2	344.5
Gromutual	1245	1195	1123	1112	1120	1127	1053	1111	1040
Guocoland	537.7	669.1	441.5	433.2	428.8	486.4	481.8	435.2	497.5
Hua Yang	221.2	696.9	204.6	201.3	204.1	280.6	286.4	202.8	257.5
I Berhad	522.8	567.5	458.6	443.9	427	483.7	482.8	571	533.7
IGB	160.5	240	153.6	151.7	153.5	170.2	171	153.2	159.5
JKG Land	691.7	560	557.4	550.8	560.7	573.5	571.7	559.8	575.5
Kenholding	713.1	783.4	651.3	653.7	783.4	716.7	717	657.2	704.4
KLCC	130	195.9	127.4	124.5	195.9	171.2	170.3	127	172.9
KSL Holding	582.8	488.9	474.7	477	476.2	488.1	470.8	503.4	474.3
LandG	641.8	839.9	523.5	513.4	512.8	650.4	651	521.1	624.4
LBI Capital	288.8	551	264.9	260	259.9	369.9	367.2	261	381.9
LBS	187.8	498.3	154.2	152.2	152	171.1	173.1	151.9	171.5
Mahsing	282.6	317.8	248.8	249.1	249.2	279.3	280.6	248.6	279.2
SBC	497.4	1325.2	431.4	426.6	432.1	499	502.6	430.4	554.6
SP Setia	250.7	276.8	220.2	214.1	213.4	236.5	243.9	213.7	239.5
UEM	767	654.7	634.8	633.8	636	652.8	655.5	634	648.2
Mean Theil-U	0.99	1.45	0.86	0.85	0.87	0.99	1	0.86	1.03

Table 6 Cont.

	STES-SE	STES-E	STES-AE	STES-E+AE	STES-ESE
AandM	408.7	502.8	408.1	959.7	458.2
Asian Pac	711	726.6	603	604.2	630.5
BCB	1044.7	1044.7	672.4	669.7	788.1
Country H	843	1083	844	847.2	992.6
Country V	2882.4	685.3	427.3	435.5	2882.4
Crescendo	282.9	293	225.7	224.9	279.4
Daiman	289.1	347.7	238	247.7	282.3
Dsr Realty	1192	1778	1188	1189	1269
Dutaland	439.4	462.8	367	366.7	428.2
EandO	382	432.8	330.3	327.7	432.9
Ecoworld	342.5	447.4	335.5	337.4	379.5
Encorp	1058	1285	861.4	861.5	1015
Enra Group	1163	1645	1161	1160	1164
Eupe	856.8	1015.3	685	686.7	829.8
Farlim	537.4	637.8	458	475.3	523.8
Global O	534.6	616.4	454.2	454.6	519.3
Glomac	334.3	343.9	276.9	278	339.8
Gromutual	966	1148	814.7	815.6	932.1
Guocoland	410.8	428.1	354.1	354.5	402.8
Hua Yang	191.7	215.4	154.5	153.9	187.1
I Berhad	418.7	437.9	348.8	351.2	420.3
IGB	148.9	154.1	113.1	112.2	150.5
JKG Land	529.5	560	514.2	510.7	524.2
Kenholding	603.7	667.3	460.7	461.7	605
KLCC	122.7	176.1	94.5	110.1	121.7
KSL Holding	457.8	486.2	377.7	376.4	453.4
LandG	452.4	840.5	390.7	390.7	443.1
LBI Capital	247.2	259.3	186.9	188.4	241.8
LBS	149.2	150.2	124.3	123.5	149.4
Mahsing	239.8	253.9	201	200.9	239.3
SBC	327.9	432	326.1	326.9	381.7
SP Setia	208.5	216.1	192	166.2	236.6
UEM	596.4	630.5	503.8	504.1	584.8
Mean Theil-U	0.8	0.91	0.67	0.69	0.8

Table 7 Average ranking of model (volatility forecasting performance) based on MAE (Optimized by MAE)

	Mean Theil-U Ranking	Average Ranking of each Method	Total MAE Ranking
RW	10	13	10
naïve forecast	14	14	14
MA30	6	8	5
EWMA (0.06)	5	5	3
EWMA (opt)	8	7	8
GARCH	11	11	11
GJR	12	11	13
IGARCH	7	6	6
EGARCH	13	10	12
STES-SE	3	4	7
STES-E	9	9	9
STES-AE	**1**	**1**	**1**
STES-E+AE	2	2	2
STES-ESE	4	3	4

CONCLUSION

Volatility forecasts are useful for risk management. Many financial practitioners and academicians have been attempting to look for a better solution to study the volatility patterns in the financial market. In assessing investment risk, volatility forecasting can affect the capital allocation of investors in diversifying their investment risk even across the regions.

One of the possible solutions to get through the price volatility characteristic is volatility forecasting. Nowadays, there are many existing models (random walk, naïve, exponential smoothing, GARCH family model and more) and newly proposed methods (such as STES method and more) available for volatility forecasting. However, there is still lack of empirical evidence on which volatility forecasting model could provide more reliable and accurate volatility forecasts in varies area of study. For example, different volatility forecasting models may perform better in the different set of data study, period, and industry. Thus, it is essential for researches conducted on the different set of data, different period of data, different industry and especially more in developing countries. This is to learn their volatility characteristic and followed by to improve the accuracy of the volatility forecasting models. In this study, we have conducted an empirical study on Malaysian real estate stock market volatility forecasting (individual price return volatility series).

As conclusion, newly proposed model, STES method, is found better in providing volatility forecasting accuracy among the volatility forecasting models. The result is more convincing evidence when it was suggested by not only one, but three evaluation methods (mean Theil-U, average ranking of each method and total MAE ranking) to be the more appropriate volatility forecasting model (optimized by MAE) in this study.

Furthermore, it is interesting that, GARCH family model which is found good in in-sample modelling is not necessarily good in out-of-sample volatility forecasts. In the in-sample observation, the average ranking has suggested a different model, GJR and GARCH model to be the best model (best suit) based on different evaluation methods. In this study, STES method (STES-AE) outperformed other methods in forecasting the volatility of Malaysian real estate stocks.

Lastly, future studies can be conducted on different models or by adding in economic variables to find out which economic variables may have influences or have impacts on the volatility forecasting performance. Likewise, not only the added in variables can provide better volatility forecasting accuracy to the models, but also if the current outperformed STES method (STES-AE) volatility forecasting accuracy can be further improved (not only the best) with the right variables.

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ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to all those who (included editors) provided me the possibility to complete this study. A special gratitude I give to my supervisor, Dr. Choo Wei Chong, who introduced me to the Methodology of work and has been teaching me since I met him.

Furthermore, I would also like to thanks Dr. Serene Ng Siew Imm and Prof. Annuar Md Nassir especially Dr. Serene Ng who has been giving me helps, guidance's and mentality support all these times. A special thanks to Dr. Law Siong Hook, who gave me suggestions and a "Bible" comments to me after my proposal defence.

In addition, I would like to thank my friend Gao XinRu (special friend), Mr. Wan, MengLin, Joe Leong, Yan Ling and more being comrade all these times. Last but not least, many thanks to Liaw Ai Yen (proof-reader) and my family who has been supporting my "wish" all these times, even though it has been taken a very long time.