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Modeling the volatility of Asian REIT markets

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ABSTRACT

This paper analyzed the volatility behavior of Asian real estate investment trust (REIT) markets. The autoregressive conditional heteroscedasticity (ARCH)-family models were applied for the purpose of conducting the in-sample fitting test and out-of-sample forecasting test. Results showed that the fractional integrated EGARCH model was the best model in forecasting the volatility for most of the Asian REIT markets. The outcome of this study would be useful for REIT investors in understanding the volatility of the Asian REIT markets. Similarly, policy-makers can also make use of this information to create derivate pricing for the future.

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Introduction

A considerable number of literature have worked on analyzing the return characteristics of real estate investment trusts (REITs). However, the number of literature that addresses the volatility behavior of REITs appears to be relatively scarce. Information addressing an asset's volatility is important for investors as this can help them to manage their risk management portfolios. Previous studies which look at REITs' volatility tend to focus on the REITS of the United States of America (US-REITs). Such information drawn from the US-REITs may not be helpful in determining the volatility of other REIT markets due to various reasons. The REIT markets in Asia, for instance, are different from the US-REITs in structure. Moreover, each of the Asian REITs markets is not similar to each other in terms of their asset management structure, geographic restrictions of underlying assets, real estate development allowance, gearing restrictions as well as dividend payout requirements (Newell, 2012). From this angle, it is reasonable to argue that the volatility foresting capability of a model could be different across different REIT markets, particularly those in Asia.

With this possibility in mind, the current study will thus attempt to measure the performance of the autoregressive conditional heteroscedasticity (ARCH)-family models using them to forecast the volatility of the Asian REIT markets. In addition, this study determines whether or not the forecasting results are different across the Asian REIT markets as there is a difference in terms of market structures and market capitalization across the Asian REIT markets. This study also aims to determine if the long memory behavior was noted in the volatility of the Asian REIT markets. This is because such behavior has been consensually

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noted in the US-REITs (Zhou & Kang, 2011) as well as in Asian property companies (Liow, 2009; Zhou, 2011).

This study contributes to the existing literature by demonstrating whether or not the long memory volatility behavior is present in the Asian REIT markets. More importantly, this study also measures the forecasting performance of the ARCH-family models on the volatility of the Asian REIT markets. The Asian REIT markets were chosen for this study as it appeared to be an alternative investment choice due to their relatively strong performance as compared to other assets. Besides, the Asian REIT markets also served as an alternative investment choice because of the stability of their performances during the global financial crisis. In this regard, the information provided regarding the volatility of the Asian REIT markets can help investors to make a better prediction of the future volatility movement of the Asian REITs markets. Consequently, such information can also be used to improve the risk management portfolio practices of investors by optimizing asset allocation in the portfolio according to the risk tolerance. In addition, the findings will also be useful for derivate pricing of REITs. Nevertheless, the comparison of the models, when used among Asian REIT markets, will determine whether or not the same model would be suitable for all countries within the same region.

Literature review

The establishment of the Asian REIT markets was followed by a proliferation of research focusing on their return performance. Even though each of the Asian REIT markets was established within the new millennium, 2000, the number of REITs listed in the specific markets as well as their market capitalizations was significantly different from one another. Moreover, each of the Asian REIT markets contained different underlying regulatory requirements. This is because the policy-makers were developing a market structure that would be deemed suitable for the development of the REIT markets. The different market structures of each of these REIT markets had led to each individual market having a unique characteristic. For instance, the Thai-REIT market was noted to be the only market that allowed investors to invest in domestic property only. In contrast, the Japan REITs and South Korea REITs did not have any gearing restrictions. The REITS in Malaysia, it was observed, appeared to be the only market that did not possess a specified dividend payout requirement. These differences make each market unique to each other.

In looking at the volatility of the Asian-REITs markets, Chang and Chen (2014) compared the performances of the Asian REIT markets and other REIT markets in the world between 02 January 2006 and 31 December 2010. They noted that the US-REITs had the highest volatility (3.25%) and the frequency dropped consecutively as it was followed by the REITs in South Korea (3.01%), Turkey (2.74%), South Africa (2.62%), the Netherlands (2.12%), Japan (2.04%), Australia (2.01%), Singapore (1.75%), Hong Kong (1.5%), France (1.45%), Greece (1.43%), Canada (1.27%), Belgium (1.16%), Taiwan (0.99%), Malaysia (0.92%), and finally, New Zealand (0.89%).These findings suggest that the Asian REIT markets have different degrees of volatility when compared to REIT markets of the world.

Past studies looking at the volatility model of REITs had mostly been focusing on the US-REITs due to their longer establishment terms (Devaney, 2001; Zhou & Kang, 2011; Asteriou & Begiazi, 2013). Such studies addressed the volatility model by assessing the degree of fit and forecasting the accuracy of the model. Devaney (2001), for instance, found that mortgage-REITs exhibit ARCH and general autoregressive conditional heteroscedasticity (GARCH) effects, based on the in-sample fitting tests. These effects were, however, not observed in equity-REITs. In contrast, Zhou and Kang (2011) noted that most of the US-REITs were fitted with exponential general autoregressive conditional heteroscedasticity (EGARCH) models, whereas the equity-REIT was mostly fitted with the GARCH model. Likewise, Asteriou and Begiazi (2013) reported that mortgage REITs was fitted to the EGARCH model, while equity REIT was better suited to the GARCH model. These differences in models suggest that the volatility behavior acts on different types of US-REITs. In looking at the out-of-sample forecast test, Zhou and Kang (2011) compared the accuracy of the two models in forecasting the return volatility of the US-REITs. Their results showed that the fractiona integrated GARCH model was among the best of the ARCH-family model in forecasting the volatility of the US-REIT return. This is because the model produced the smallest error in forecasting when compared to other ARCH-family models.

In looking at the Asian property companies, Liow and Chen (2013) tested the presence of the ARCH effects among property companies' markets in Australia, Japan, Hong Kong, Singapore, China, Taiwan, Malaysia, and the Philippines. They found that the presence of the ARCH effects in majority of the markets' volatility varied with time. Further, these studies also documented the long memory behavior of the volatility on the Asian property companies (Liow, 2009; Zhou, 2011; Razali, 2015). Liow (2009), for instance, examined the presence of long memory behavior in the conditional volatilities using the fractional integrated GARCH (FIGARCH) model. The results indicated that long memory behavior of volatility was present in the property companies of Japan, Singapore, Hong Kong, Malaysia, Taiwan, and South Korea. This outcome suggests that a long memory model should be incorporated into the volatility modeling of the Asian property companies in order to have a higher accuracy of the forecasting model.

With regards to the Asian REIT markets, research had primarily focused on examining the volatility behavior of the Asian REIT markets. Tsai, Chiang, and Lin (2010) measured the GARCH effects on the Asia Pacific REIT markets (Australia, Japan, Singapore, Taiwan, Korea, and Hong Kong). The presence of the GARCH effects was established in these markets and it implied that past conditional variance does affect the volatility of these markets. In addition, Tsai (2013) also found that the leverage effects of the volatility was only present in the REITs markets of Japan and Hong Kong. This showed that the volatility of the REIT markets does behave differently across Asia. To the best of the authors' knowledge, none of the study had performed the volatility forecasting test on Asian REIT markets. In addition, whether or not the Asian REIT markets have a long memory impact or not has not been answered by literature focusing on Asian REIT markets.

The following section reviews the models employed in this study. It is then followed by a discussion on methodology and data analysis. The result of in-sample test and out-of-sample forecast test is further discussed in the subsequent section. The final section concludes the study.

Evolution of volatility model

ARCH model was introduced by Engle (1982). It was created to incorporate the conditional heteroscedasticity issue into the model. However, due to the large number of parameters

Table 1. List of short memory and long memory models.

Short memory model	Long memory model
General ARCH (GARCH) model	Fractional integrated GARCH (FIGARCH) model
Exponential GARCH (EGARCH) model	Fractional integrated EGARCH (FIEGARCH) model
Asymmetric power ARCH (APARCH) model	Fractional integrated APARCH (FIAPACH) model

required, Bollerslev (1986) modified ARCH model to become GARCH model to permit the lags of past conditional variance.

To capture the different impact between negative and positive news on the volatility, it has led towards the creation of asymmetric ARCH model, such as exponential GARCH model (Nelson, 1991). On the other hand, the persistence of shocks towards the volatility is captured by integrated GARCH model (Engle & Bollerslev, 1986), while the fractional integrated models such as fractional integrated GARCH (Baillie, Bollerslev, & Mikkelsen, 1996) and fractional integrated EGARCH (FIEGARCH) models (Bollerslev & Mikkelsen, 1996) were used to model the influence of lagged squared innovations on the slow hyperbolic rate of decay of the conditional variance.

The following section reviews the model specification of the volatility models that were used for this study. These models were being categorized into the short memory models or long memory models as shown in Table 1. For short memory models, the correlation of the series and its lag converge to a constant when the lag becomes large. On the other hand, the effect of volatility shocks decay slowly in long memory models.

GARCH model

The ARCH model was used to measure the volatility of time series by taking the conditional heteroscedasticity into consideration (Engle, 1982). The model specification of the ARCH model is defined as:

$$r_t = \pi_0 + \sum_{i=1}^{n} \pi_i x_i + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1} \tag{2}$$

where the r_t is the conditional mean, x_i represents the independent variables, while ε_{t-1} is the error of the model.

As the ARCH model requires many parameters to model the volatility, the GARCH model was created by incorporating past conditional variance to measure the volatility (Bollerslev, 1986). In the GARCH model, conditional variance is linearly dependent on the past behavior of squared residual and the moving average amounts of its past conditional variances. The following is the specification of the GARCH model.

$$r_t = \pi_0 + \sum_{i=1}^{n} \pi_i x_i + \varepsilon_t \tag{3}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1} + \beta\sigma_{t-1}^2 \tag{4}$$

where r_t is the conditional mean while σ_t^2 is the conditional variance with restriction imposed on the parameters ω, α, and β by setting $\omega > 0$, $\alpha > 0$, $\beta > 0$.

EGARCH model

Nelson (1991) introduced the EGARCH model. It came with a new variable that distinguishes the difference of the impact between good news and bad news as negative innovation is believed to result in a higher volatility as compared to a similar magnitude of positive innovation. The specification of the EGARCH is shown below.

$$r_t = \pi_0 + \sum_{i=1}^{n} \pi_i x_i + \varepsilon_t \tag{5}$$

$$\log\left(\sigma_t^2\right) = \omega + \alpha z_{t-1} + \gamma\left(\left|z_{t-1}\right| - E|z_{t-1}|\right) + \beta \log\left(\sigma_{t-1}^2\right) \tag{6}$$

where γ is representing the asymmetric leverage coefficient to test for the volatility leverage effect and z_t is the ratio of ε_t towards σ_t.

Asymmetric power ARCH (APARCH) model

Compared with other models, the asymmetric power ARCH (APARCH) model (Ding, Granger, & Engle, 1993) was created to include many other popular GARCH variants as is noted in special cases. In the context of this study, the APARCH model is defined as below:

$$r_t = \pi_0 + \sum_{i=1}^{n} \pi_i x_i + \varepsilon_t \tag{7}$$

$$\sigma_t^\delta = \omega + \alpha\left(\left|\varepsilon_{t-1}\right| - \gamma\varepsilon_{t-1}\right)^\delta + \beta\sigma_{t-1}^\delta \tag{8}$$

where parameter δ ($\delta > 0$) is the Box–Cox transformation of the conditional standard deviation σ_t, while γ test the leverage effect. The APARCH model reflects several ARCH model under circumstances for when $\delta = 2$. When $\gamma = 0$, it reflects a GARCH(1,1) model. When $\delta = 2$, a GJR(1,1) model is represented. Thus, it is noted that the APARCH model can capture different features in volatility behavior at the same time.

FIGARCH model

The FIGARCH model describes the auto-correlations in volatility decay at a slow hyperbolic rate. It is different from the exponential rate that is described by the GARCH model. This particular model was proposed by Baillie et al. (1996) and it is specified as below:

$$r_t = \pi_0 + \sum_{i=1}^{n} \pi_i x_i + \varepsilon_t \tag{9}$$

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \left[1 - (1-\beta L)^{-1}(1-\varphi L)(1-L)^d\right]\varepsilon_t^2 \tag{10}$$

where $0 \leq d \leq 1$, $\omega > 0$, $\varphi, \beta < 1$, L represents the lag operator,

where the new parameters are introduced to the GARCH model,

- B^j and B^i, the backshift operator.
- d, the fractional differencing parameter.

The fractional differencing parameter, d, is used in the FIGARCH model to capture the long memory features of financial volatility. If $0 \leq d \leq 1$, then the conditional volatility will decay at a slow hyperbolic rate and this shows that there is a long memory symptom.

FIEGARCH model

Bollerslev and Mikkelsen (1996) proposed an expansion of the FIGARCH model which can capture the asymmetric effect and this model was named the FIEGARCH.

$$r_t = \pi_0 + \sum_{i=1}^{n} \pi_i x_i + \varepsilon_t \tag{11}$$

$$\log\left(\sigma_t^2\right) = \omega + \left[1 - \sum_{j=1}^{q} \beta_j B^i\right]^{-1} (1-B)^{-d} \left[1 + \sum_{i=1}^{p} \alpha_i B^i\right] g\left(\varepsilon_{t-1}\right) \tag{12}$$

The way of defining the variables are similar to the FIGARCH model except that:

- d, has to be a real number between $(-.5, .5)$
- $g\left(\varepsilon_t\right) = \lambda_1\varepsilon_t + \lambda_2\left(\left|\varepsilon_t\right| - E\left(\left|\varepsilon_t\right|\right)\right)$ with λ_1 and λ_2 are new parameters, asymmetric effect will be captured by $\lambda_{1.}$

The condition for d will be $d < 1$, but $d \neq 0$. ($d = 0$ refer to conventional EGARCH).

Fractional integrated APARCH (FIAPARCH) model

The APARCH model was modified by Tse (1998) to become the fractional integrated APARCH (FIAPARCH) model which addresses the long memory effect by incorporating the fractional filter, $(1 - L)^d$.

$$r_t = \pi_0 + \sum_{i=1}^{n} \pi_i x_i + \varepsilon_t \tag{13}$$

$$\sigma_t^\delta = \omega + \left\{1 - [1-\beta(L)]^{-1}\alpha(L)(1-L)^d\right\}\left(\left|\varepsilon_t\right| - \gamma\varepsilon_t\right)^\delta \tag{14}$$

The FIAPARCH model provides flexibility in conditional variance specification by: (i) allowing asymmetric response, (ii) determining the power of return, and (iii) allowing long memory volatility dependence. The leverage effect is shown by the term $(|\varepsilon_t| - \gamma\varepsilon_t)^{\delta}$ when $\gamma \neq 0$. Positive innovations can increase the volatility to a lesser degree than a negative innovation when γ falls between 0 and 1 and vice versa for the γ range between −1 and 0. At $\gamma = 0$, the reading shows that the positive and negative innovation of the same magnitude has the same impact on volatility (Franke, Härdle, & Hafner, 2011). The FIAPARCH model is useful for modern financial economics such as the pricing of optimal portfolio allocations and long-term options (Conrad, Karanasos, & Zeng, 2011).

Data and methodology

This study employed the Standard and Poor daily total return index for the Japan, Hong Kong, Singapore, Malaysia, and Taiwan REIT markets. It also uses self-constructed daily total return index for the Thailand and South Korean REIT markets which use weighted capitalization methods. The sampling period covers the date of the establishment of REITs until 31 December 2014 (shown in Table 2). The daily data were chosen instead of monthly data because the daily data give a better forecast accuracy of the volatility as compared to the monthly data (Andersen, Bollerslev, & Lange, 1999). The index data were then converted to continuous compounded return using a log differencing method.

$$r_t = \log\left(p_t / p_{t-1}\right) \tag{15}$$

Data were split into two segments. The first segment was used for the in-sample fitting test, while the second segment was used for the out-of-sample forecasting test. The in-sample fitting test was then conducted on each market by excluding the last 120 observations from the total sample size which will be used for out-of-sample test. As for the last 120 observations, the out-of-sample forecasting test was then conducted based on the following days: 1-day, 5-day, 10-day, 15-day, 20-day, and 25-day forecast which was computed by rolling over the data frame windows to re-estimate the model and to generate the forecast. Thus, the total number computed for 1-day, 5-day, 10-day, 15-day, 20-day, and 25-day were 120, 116, 111, 106, 101, and 96, respectively. The forecast horizon was decided by referring to the guideline suggested by Figlewski (1997) who says that the forecast accuracy of daily data drops with forecast horizon that is longer than 24 months.

Table 2. Description of REIT index.

Market	Commence date
Japan	28 September 2001
Singapore	30 June 2003
Hong Kong	30 June 2004
Malaysia	31 October 2006
Thailand	29 October 2003
Taiwan	31 January 2006
South Korea	23 May 2001

Model evaluation technique

The Schwartz information criterion (SIC) was used to assess the degree of fit for the models. The model with the smallest SIC values is considered as the best fitted model. The SIC was used instead of the Akaike information criterion as the latter tends to choose the less parsimonious model.

The forecasting performance of the model was assessed based on the forecast accuracy that was calculated based on the mean absolute error (MAE).The MAE is used instead of the root mean squared error to assess the model ranking because of its simplicity of specification (Willmott & Matsuura, 2005). The root mean squared error would be more appropriate when the error of the model was assumed to fall under the Gaussian distribution (Chai & Draxler, 2014).

$$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} |\sigma_t^2 - \hat{\sigma}_t^2| \tag{16}$$

$\hat{\sigma}_t^2$ represents the forecasted volatility, while σ_t^2 represents the true volatility, with n equal to the total number of forecast. The true volatility was calculated by taking the square of the difference between the current return and the average of return. A lower MAE value implies a better forecast accuracy of the model in relation to other models.

Result and discussion

The descriptive statistics of the data are shown in Table 3. The statistics indicate that the Hong Kong REIT market has the highest average daily return of .058%. This is followed by the REIT markets in Singapore (.052%), Japan (.039%), Taiwan (.039%), Malaysia (.030%), Thailand (.017%), and South Korea (.017%). Nonetheless, the standard deviation of the REIT markets return ranged between .630 and 2.744%. This suggests that each of the Asian REIT markets has a varying degree of average volatility when compared to each other. In addition, all of the series are found to be stationary at level. Thus, no further transformation is needed to make the series become stationary prior to further testing.

Besides all that has been discussed, different specifications of the models were also tested using different orders of p and q values so as to determine the best specification of the model. As shown in Table 4, the model with $p = 1$ and $q = 1$ was chosen for the purpose of using the most parsimonious model (Zhou & Kang, 2011) in the context of this study. This was also because the difference of the log-likelihood values between the GARCH (1.1) model and other models was small. Table 4: Comparison on different order of the models

In-sample fitting test

The degree of fit noted for the model was assessed using the SIC criteria. The model with the smallest SIC values is considered as the best fitted model. As shown in Table 5, most of

Table 3. Descriptive statistics.

	Japan	Singapore	Hong Kong	Malaysia	Thailand	Taiwan	South Korea
Mean	.039	.052	.058	.030	.017	.039	.017
Standard Deviation	1.387	1.310	1.220	1.047	.630	.652	2.744
Prob. of ADF test	.000***	.000***	.000***	.000***	.000***	.000***	.000***

Note: Descriptive Statistics generated basic on the individual daily return. *** represents significant at 1% level.

Table 4. Comparison on different order of the models.

Model	Country						
	Japan	Singapore	Hong Kong	Malaysia	Thailand	Taiwan	South Korea
GARCH(1,1)	−4643.010	−4035.704	−3848.050	−2911.992	−2090.958	−1534.407	−7872.051
GARCH(1,2)	−4631.307	−4033.602	−3846.201	−2910.660	−2055.243	−1532.387	−7860.229
GARCH(2,1)	−4637.331	−4033.861	−3847.209	−2909.524	−2074.213	−1533.561	−7872.446
GARCH(2,2)	−4642.465	−4032.061	−3846.901	−2909.345	−2052.888	−1533.026	−7850.225
EGARCH(1,1)	−4624.063	−4029.878	−3864.603	−2925.387	−2064.355	−1510.644	−7934.234
EGARCH(1,2)	−4619.155	−4029.570	−3853.932	−2923.337	−2058.231	−1509.326	−7975.805
EGARCH(2,1)	−4618.235	−4018.704	−3861.626	−2924.224	−2063.899	−1509.206	−7841.564
EGARCH(2,2)	−4613.977	−4031.774	−3852.370	−2923.006	−2041.579	−1509.042	−7826.113
APARCH(1,1)	−4636.507	−4033.032	−3847.395	−2910.565	−2084.995	−1503.764	−7860.642
APARCH(1,2)	−4618.229	−4025.081	−3840.125	−2905.658	−2048.787	−1497.814	−7859.759
APARCH(2,1)	−4629.736	−4028.586	−3846.548	−2907.591	−2068.577	−1501.603	−7862.028
APARCH(2,2)	−4616.131	−4023.317	−3842.951	−2904.567	−2047.238	−1500.317	−7836.361
FIGARCH(1,*d*,1)	−4621.912	−4028.739	−3831.168	−2966.863	−2048.909	−1529.169	−7841.356
FIGARCH(1,*d*,2)	−4622.272	−4028.937	−3830.897	−2970.019	−2050.216	−1529.543	−7841.174
FIGARCH(2,*d*,1)	−4622.241	−4028.857	−3830.744	−2966.147	−2052.906	−1529.799	−7840.780
FIGARCH(2,*d*,2)	−4617.890	−4025.950	−3830.657	−2970.519	−2050.259	−1520.629	−7843.202
FIEGARCH(1,*d*,1)	−4622.744	−4031.224	−3849.716	−2893.401	−2036.090	−1502.073	−7803.124
FIEGARCH(1,*d*,2)	−4619.371	−4028.533	−3849.361	−2888.636	−2036.144	−1504.381	−7802.800
FIEGARCH(2,*d*,1)	−4615.631	−4024.766	−3849.670	−2089.865	−2035.526	−1495.071	−7803.099
FIEGARCH(2,*d*,2)	−4610.004	−4024.778	−3849.348	−2165.469	−2010.819	−1480.594	−7801.471
FIAPARCH(1,*d*,1)	−4618.703	−4025.722	−3830.944	−2893.512	−2041.966	−1501.475	−7833.225
FIAPARCH(1,*d*,2)	−4619.042	−4025.922	−3830.680	−2916.157	−2043.942	−1502.371	−7834.950
FIAPARCH(2,*d*,1)	−4619.003	−4025.796	−3830.472	−2824.841	−2045.299	−1501.553	−7831.656
FIAPARCH(2,*d*,2)	−4614.234	−4020.346	−3830.343	−2945.815	−2042.901	−1496.681	−7833.813

Note: Each entry denoted the log likelihood value generated from the model.

Table 5. Comparison between models for in-sample fitting test.

Model	Japan	Singapore	Hong Kong	Malaysia	Thailand	Taiwan	South Korea
GARCH	2.794	2.813	2.953	2.916	1.510	1.407	4.598
EGARCH	2.795	2.820	2.970	2.936	1.524	1.390*	4.584
APRACH	2.803	2.816	2.958	2.927	1.512	1.394	4.599
FIGARCH	2.789*	2.810*	2.943*	2.981	1.483	1.405	4.585
FIEGARCH	2.790	2.818	2.963	2.913*	1.478*	1.395	4.568*
FIAPARCH	2.792	2.814	2.949	2.918	1.480	1.398	4.585

Note: Each entry denotes the SIC value. The model with lowest SIC value for each country is marked with *.

the REIT markets appear to be best fitted with long memory models except for the Taiwan REIT market which was best fitted to the EGARCH model. Among the long memory models, the FIGARCH model was noted to be the most suitable model for the REIT markets in Japan, Singapore, and Hong Kong. The finding implies that a similar level of volatility behavior exists among these three markets. In contrast, the REIT markets in Malaysia, Thailand, and South Korea were best fitted with the FIEGARCH model. This implies that the market responded asymmetrically towards the positive and negative shocks. The result of this study is contrary to the findings of Tsai (2013), who only found the asymmetric effect to exist in the REIT markets of Japan. Such differences noted can be attributed to the difference in study period whereby a longer time frame may be more preferable for revealing the volatility behavior.

This study confirms the findings of Liow (2009) and Zhou (2011) which indicate the long memory impact of the Asian property companies, as the Asian REIT markets also seems to be exhibiting the long memory volatility behavior. A similar outcome like this implies that the impact of past volatility can influence the future volatility of the indirect real estate markets in Asia through a slow decaying process. In other words, the impact of past volatility has a long-lasting impact on the volatility of the future.

Out-of-sample forecast test

Table 6 tabulates the results of the out-of-sample forecasting test. As for the REIT markets in Japan, Singapore, and Hong Kong, the FIEGARCH was noted to outperform other models and this was accomplished through the smallest error noted in the forecast. The three countries of Japan, Singapore and Hong Kong had the largest market capitalization when compared to other Asian REIT markets and this could imply that the FIEGARCH model

Table 6. Forecast error statistics.

Country	Model	1-day ahead forecast	5-day ahead forecast	10-day ahead forecast	15-day ahead forecast	20-day ahead forecast	25-day ahead forecast
Japan	GARCH	1.06990	1.0991	1.04729	.79290	.90825	.96958
	EGARCH	1.01773	.81458	.77428	.72562	.79116	.82533
	APARCH	.95739	.94178	.88909	.78400	.8978	.98231
	FIGARCH	1.08363	.83148	.76934	.6694	.68811	.71497
	FIEGARCH	.95325*	.66349*	.65502*	.6533*	.67953*	.69981*
	FIAPARCH	.97123	.76300	.71723	.66629	.68551	.71446
Singapore	GARCH	.12841	.14378	.16071	.17789	.19471	.23465
	EGARCH	.12793	.13313*	.14211	.14179	.13756	.14704
	APARCH	.12888	.14376	.16072	.17487	.18616	.22451
	FIGARCH	.12657	.14021	.15506	.16096	.16619	.19118
	FIEGARCH	.12654*	.13382	.14139*	.13905*	.13453*	.14113*
	FIAPARCH	.12762	.14124	.15455	.15754	.16004	.17900
Hong Kong	GARCH	1.27672	1.25942	1.40920	1.49200	1.56397	1.65502
	EGARCH	1.17657	1.17298	1.31033	1.39535	1.51821	1.68023
	APARCH	1.29185	1.26384	1.41462	1.49118	1.55325	1.62594
	FIGARCH	1.28155	1.13083	1.16758	1.16646	1.15815	1.13934
	FIEGARCH	1.16798*	1.01957*	1.05404*	1.04747*	1.08872*	1.0532*
	FIAPARCH	1.26847	1.12083	1.15918	1.15788	1.15132	1.12964
Malaysia	GARCH	.71492	.95790	1.06779	1.10095	1.10360	1.09257
	EGARCH	.84336	1.07412	1.13194	1.14550	1.14224	1.12947
	APARCH	.69498*	.9388*	1.03868*	1.07171*	1.07772*	1.06629*
	FIGARCH	1.12154	7.44553	21.3312	43.865	68.4703	4.57534
	FIEGARCH	.77050	1.14935	1.34535	1.47297	1.5446	1.58903
	FIAPARCH	.79724	1.12623	1.46832	1.80042	1.86378	1.93294
Thailand	GARCH	.04524	.04484	.04554	.04779	.04915	.05053
	EGARCH	.04474	.04463	.04583	.04784	.04899	.05090
	APARCH	.04508	.04470	.04509*	.04707*	.04871*	.04994*
	FIGARCH	.04463	.04523	.04769	.04918	.05066	.05150
	FIEGARCH	.04432*	.04451	.04643	.0486	.05087	.05300
	FIAPARCH	.04456	.04449*	.04631	.04819	.04943	.05082
Taiwan	GARCH	.08419	.10932	.17954	.29819	.49314	.79084
	EGARCH	.08265	.09189*	.11759*	.1523	.19129	.22922*
	APARCH	.08354	.11086	.19359	.33637	.56472	.87048
	FIGARCH	.08326	.09601	.13114	.17694	.23565	.30713
	FIEGARCH	.08360	.09401	.11935	.15189*	.1904*	.23191
	FIAPARCH	.08254*	.10339	.15418	.22445	.30727	.40175
South Korea	GARCH	35.87509	35.951	37.2313	38.7751	41.2187	41.3444
	EGARCH	35.79148	42.7395	47.6719	49.6382	55.0561	58.0916
	APARCH	35.85174	37.6296	42.1585	44.1043	50.3244	53.6021
	FIGARCH	6.04448*	5.98416*	5.66324*	5.84045*	6.1077*	6.19853*
	FIEGARCH	26.58536	33.1907	35.4117	37.4589	39.4763	41.0324
	FIAPARCH	27.15553	28.6892	29.3327	30.1114	30.251	30.3675

Note: The lowest value for each error measurement criteria is marked with *.

is better suited to markets with large market capitalizations. In contrast, the APARCH model appears to produce the lowest forecast error for the REIT markets in Malaysia and Thailand. This suggests that the volatility of the REIT market in Malaysia could be similar to the volatility of its neighboring REIT markets which also carry similar smaller market capitalizations. Further, it is observed that REITs with a smaller market capitalization are more likely to influence each other. The FIGARCH model only appeared to be the best forecasting model for the REITs in South Korea but not others. This outcome could be attributed to the fact that REIT markets in South Korea have a corporate-restructuring pattern that is not available in other Asian REIT markets. Lastly, it appears that the models' performances vary with different forecast horizons of the Taiwan REIT markets. This outcome could be attributed to the relatively shorter data time frame used for the REIT markets in Taiwan. Generally, the EGARCH model produced the smallest forecast error in the REIT markets of Taiwan most of the time .The results of this study is unlike the findings of Zhou and Kang (2011), who noted that the FIGARCH model only appears to be the best volatility forecasting model for REIT markets in South Korea. Overall, these results have clearly shown that the long memory model has a superior performance in forecasting the volatility behavior among most of the Asian REIT markets.

In addition, it was observed that the best fitted model does not yield the best forecasting performance. This outcome is similar to the findings of Shamiri and Isa (2009), who noted that the best fitted model does not necessarily produce the highest forecast accuracy on the volatility behavior of stock markets. The current study highlights the importance of conducting out-of-sample forecasting since in-sample fitting test only measures the historical performance of models in fitting the volatility of the markets. Further, it may be impractical to measure the forecasting performance in practice when under restricted circumstances such as when the sample size is small. Under that circumstance, the best fitted model to be considered would be the best performing model (Kosapattarapim, Lin, & McCrae, 2011).

Conclusion

This study assessed the volatility behavior of the Asian REIT markets from the perspective of in-sample fitting test and out-of-sample forecasting test. It was found that the FIEGARCH model is the best performing model in terms of model fitting and model forecasting for most Asian REIT markets. Based on the results, it can be said that the volatility behavior for a market is likely to change over time if a best fitted model of the in-sample fitting test does not produce the best forecasting performance during out-of-sample forecasting test.

Based on the findings, it is proposed that volatility information on markets be updated on a regular basis. This is to enhance knowledge for those involved. From the outcome of this study, it can be noted that the volatility behavior of the Asian REIT markets and the US-REIT markets are different when the current results are compared to the findings of Zhou and Kang (2011). The current results inform investors to access their portfolio preference first before investing in REIT markets, and that they should not take one market as the proxy for another market.

The implication that can be drawn from this study is that the information provided can enhance investors' understanding of market behaviors. For instance, the EGARCH model informs investors on the need to be cautious about the bad news in the markets as their REIT stocks might fluctuate to a higher level than what past good news had indicated. Moreover, the long memory behavior drawn from this study implies that the volatility of the Asian REIT markets was decaying slowly. In addition, the results of this study offer information for derivate pricing of REITs by providing the forecast accuracy of the ARCH-family models which demonstrates the volatility of the Asian REIT markets. For a more in-depth understanding of the REIT markets, future research can be focused on REIT markets that are out of the Asian region.

Disclosure statement

No potential conflict of interest was reported by the authors.

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