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A COMPARISON OF FORECASTING MODELS FOR ASEAN EQUITY MARKETS

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ABSTRACT

This paper compares six models for forecasting the performance of the ASEAN equity markets of Malaysia, Singapore, Thailand, Indonesia and the Philippines before, during and after the Asian financial crisis. In the pre-crisis period, the OLS, ARCH-M and TARCH models have better forecasting performance than the other models. In the crisis period, the ARCH-M model has the best forecast performance for three markets, while the remaining two markets are best forecast with the random walk model. However, in the post-crisis period, the TARCH and EGARCH models are found to be the most suitable models. The different variants of the GARCH model adequately captured the time-varying returns volatility. But the asymmetry of the market returns is not significant in all the markets modelled by the TARCH and EGARCH models.

Key words: ARCH-M, GARCH, TARCH, EGARCH, random walk, Asian financial crisis.

INTRODUCTION

A stock market provides an added dimension of investment opportunity for both individual and institutional investors and, thus, the nature and behaviour of stock market returns are of interest to academic researchers and market practitioners. One area of particular interest is forecasting whereby the interested parties aim to exploit information contained in the past realisations of a vector of time series for the purpose of predicting future price movements.

Such an endeavour, however, challenges the efficient market hypothesis, which in turn is closely tied to the random walk concept. Random walk theory asserts that stock price movements are unpredictable and do not follow any patterns or trends over time. Emphatically, in a perfectly efficient market, historical returns would not offer any useful insight for speculating on future price movements. Indeed, many of the earlier studies on the stock markets of developed countries (see Kendall (1953), Fama (1965a, b), Granger and Morgenstern (1963), Godfrey et al. (1964), Sharma and Kennedy (1977) and Cooper (1982)) indicated that their stock returns are random in nature and hence these findings lend support to the efficient market hypothesis.

Using new statistical methods, however, the more recent studies provide evidence against the random walk behaviour of stock prices. For example, Lo and Mackinlay (1987),

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Poterba and Summers (1988) and Frennberg and Hansson (1993) found that stock returns are mean-reverting in the long run and are therefore, to a certain extent, predictable. Even for short horizon returns, there is some evidence contrary to the efficient market hypothesis.

Empirical studies have concluded that large changes in prices tend to be followed by larger changes in either direction. This implies that volatility must be predictably high after large changes. The introduction of time-varying volatility in financial time series data by Engle (1982), and subsequent development by Bollerslev (1986), had led to the formulation of the autoregressive conditional heteroscedasticity (ARCH) model and its many variants (see Engle et al. (1987), Glosten et al. (1993) and Nelson (1991)). Using these models, Bollerslev (1987), Akgiray (1989), Tse and Tung (1992), Franses and van Dijk (1996), Walsh and Tsou (1998) and McMillan et al. (2000) obtained findings that pose yet another challenge to the validity of random walk in stock returns.

Mixed findings are obtained on stock price behaviour for the ASEAN stock markets. Laurence (1986), Saw and Tan (1989), Mansor (1989) and Kok and Goh (1994a) found that stock returns in Malaysia basically followed a random walk. Moreover, in a separate study Kok and Goh (1994b) detected the presence of mean-reverting behaviour in the Malaysian stock returns while Mansor (1999) and Pan et al. (1999) showed that the returns displayed ARCH effects. However, a study on the stock returns in Singapore by Saw and Tan (1986) concluded that these returns did not exhibit any significant random walk behaviour. A similar finding was obtained by Sareewiwathana and Isbell (1985) on the Thailand market.

When a random walk model is used for forecast, it would yield a naïve forecast of no change. Although various models have been developed to account for the time-varying volatility in financial time series data, it remains to be seen whether these models would provide a better forecast than that of the random walk. This paper, therefore, compares the forecast performance of the random walk model and the other models that capture the time-varying volatility in stock returns for each of the five ASEAN stock markets of Malaysia, Singapore, Thailand, Indonesia and the Philippines. In particular, the comparison is made for each of the three periods as divided by the Asian financial crisis that first occurred in 1997, namely, the pre-crisis period, the crisis period and the post-crisis period. The results of this study have implications for weak form market efficiency, particularly for asset pricing and hedging since, for example, the Kuala Lumpur Stock Exchange (KLSE) Composite Index is used as the underlying index for stock index futures trading.

The remainder of this paper is structured in the following format. Section 2 explains the data and the methodology used in the study. In Section 3 we discuss the findings and in the concluding chapter we draw appropriate conclusions and implications of the study.

DATA AND METHODOLOGY

The data used in the study are the daily closing values of the Kuala Lumpur Stock Exchange Composite Index, Singapore Stock Exchange All-Share Index, Stock Exchange of Thailand Index, Jakarta Composite Index and the Philippines Composite Index over the period extending from 2 January 1992 to 12 August 2002. The data are obtained from the financial data provider Bloomberg. The daily market returns are computed as log index relatives.

Three periods are identified in this study: 2 January 1992 to 31 January 1997, 1 February 1997 to 30 September 1998 and 1 October 1998 to 12 August 2002. In relation to the Asian financial crisis, these 3 periods correspond approximately to the pre-crisis period, the crisis period and the post-crisis period, respectively.

Except for the "holdout sample" reserved for the purpose of examining the out-of-sample forecasting performance, the six forecasting models are estimated for each period by using the daily closing values in that period. The "holdout sample" comprises the daily closing values of the last 20 trading days in each period. In other words, the estimated models are used to generate ex-post forecasts of the daily closing values for these last 20 trading days, with the actual values known. By comparing these ex-post forecasts with the actual values, the model's forecasting ability is evaluated.

If P_t represents the stock index of a market at time *t*, the return of the index at time *t* is computed as follows:

$$r_t = \ln (P_t \;/\; P_{t-1})$$

Advocates of the efficient market hypothesis assert that stock prices are essentially random and therefore there is no scope for profitable speculation in the stock market. Thus, in most studies, a random walk model without drift, which is simply an AR (1) process with a unit coefficient, is often used as the fundamental forecasting model. However, the daily rates of returns on common stock generally have a slightly upward bias or drift, given the long-term positive expectation for rates of returns. So in this study, we shall allow for this possibility of a stochastic trend by incorporating a drift term. Therefore, a random walk with drift is used instead. This random walk (RW) model is given as follows:

$$r_t = \mu + \varepsilon_t \qquad (1)$$

where μ is the mean value of the returns, which is expected to be zero; ε_t is the error term with zero mean and is not autocorrelated over time.

The second forecasting model is the ordinary least squares (OLS) model which allows for a lag dependence structure by including the lagged term of the index returns. Its equation is given by

$$r_t = \mu + \alpha\, r_{t-1} + \varepsilon_t \qquad (2)$$

Through this OLS model, the conditional mean of the stock index returns is modelled.

In addition to estimating the mean equation (2), it is also pertinent to model the conditional variance of the returns. The next four models take into account this time-varying volatility.

The generalized ARCH, or GARCH, process, as proposed by Bollerslev (1986), is extensively applied in financial time series analysis. In this study, GARCH (1, 1), which is the most popular specification, is used. This model is given by the following set of equations:

$$r_t = \mu + \alpha\, r_{t-1} + \varepsilon_t \qquad (3)$$

$$\varepsilon_t = z_t\, \sigma_t$$

$$\sigma_t^2 = a + b\,\varepsilon_{t-1}^2 + c\,\sigma_{t-1}^2 + w_t$$

where z_t is a stochastic variable not autocorrelated in time, and has a standardized normal distribution; σ_t^2 is the conditional variance of the returns and w_t is a random component with the properties of white noise. The remaining three models are variations of model (3).

The ARCH-in-Mean (ARCH-M) model, proposed by Engle et al. (1987), is obtained by introducing the conditional standard deviation into the mean equation of model (3). This model is commonly used in situations where the expected returns on an asset is related to the expected asset risk. The conditional standard deviation acts as a proxy for the risk and the estimated coefficient on the expected risk is taken as a measure of the risk-returns tradeoff. This ARCH-M (1, 1) model is given as follows:

$$r_t = \mu + \alpha r_{t-1} + \beta \sigma_t + \varepsilon_t \qquad (4)$$

$$\varepsilon_t = z_t \sigma_t$$

$$\sigma_t^2 = a + b\varepsilon_{t-1}^2 + c\sigma_{t-1}^2 + w_t$$

It is often observed that downward movements in the equity markets are followed by higher volatilities than upward movements of the same magnitude. This asymmetric effect is commonly referred to as the leverage effect. In the presence of such an effect, the GARCH model would be deemed inadequate to model the volatility. The Threshold ARCH (TARCH) and Exponential ARCH (EGARCH) models, proposed by Glosten et al. (1993) and Nelson (1991), respectively, which allow for such asymmetric shocks to volatility, would then be more suitable.

The TARCH (1, 1) model is given as follows:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t \qquad (5)$$

$$\varepsilon_t = z_t \sigma_t$$

$$\sigma_t^2 = a + b\varepsilon_{t-1}^2 + c\varepsilon_{t-1}^2 \xi_{t-1} + d\sigma_{t-1}^2 + w_t$$

where $\xi_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $\xi_{t-1} = 0$ if $\varepsilon_{t-1} > 0$.

The TARCH model is formulated on the assumption that unexpected changes in the market returns, which are expressed in terms of ε_t, have a different impact on the conditional variance of the returns. Good news is associated with an unforeseen increase and hence will contribute to the variance through the coefficient *b*. An unforeseen fall, which constitutes bad news, will induce an increase in volatility through the coefficient ($b + c$). Thus, a non-zero value of the coefficient *c* implies the asymmetric nature of the returns, while a positive value of *c* indicates the presence of leverage effect.

The exponential nature of the conditional variance in the EGARCH model ensures that external unexpected shocks will exert a stronger influence on the predicted volatility than they would in the TARCH model. The EGARCH (1, 1) model is given as follows:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t \qquad (6)$$

$$\varepsilon_t = z_t \sigma_t$$

$$\ln(\sigma_t^2) = a + b\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + c\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + d\ln(\sigma_{t-1}^2) + w_t$$

As in the TARCH model, the non-zero value of *c* will indicate an asymmetric effect in the returns and the presence of leverage effect is shown by its negative value.

The models are evaluated in terms of their ability to forecast future returns. Several measures are used in comparing forecasting performance of different models. The most common measure is the mean squared error (MSE). Often the square root of MSE (RMSE) is used so as to preserve the units. The less popular, but nonetheless common, measures are the mean absolute error (MAE) and the mean absolute percentage error (MAPE). Another common criterion used in comparing performance of forecast models is the Theil inequality coefficient. Its value always lies between zero and 1, where zero indicates a perfect fit. These four forecast error statistics are computed as follows:

RMSE: $\sqrt{\frac{1}{20}\sum_{t=T+1}^{T+20}\left(\hat{P}_t - P_t\right)^2}$	MAE: $\frac{1}{20}\sum_{t=T+1}^{T+20}\left\lvert\hat{P}_t - P_t\right\rvert$
MAPE: $100 \times \left(\frac{1}{20}\sum_{t=T+1}^{T+20}\left\lvert\frac{\hat{P}_t - P_t}{P_t}\right\rvert\right)$	Theil Inequality Coefficient: $\dfrac{\sqrt{\frac{1}{20}\sum_{t=T+1}^{T+20}\left(\hat{P}_t - P_t\right)^2}}{\sqrt{\frac{1}{20}\sum_{t=T+1}^{T+20}\hat{P}_t^{\,2}} + \sqrt{\frac{1}{20}\sum_{t=T+1}^{T+20}P_t^{\,2}}}$

where *T* is the number of observations in the sample for estimation and the ex-post forecasts constitute observations $T + 1$ to $T + 20$. P_t and $\hat{P}_t$ respectively denote the actual and forecasted daily closing values for the stock index of a market in period *t*.

The "best" model for forecasting for a particular period, as indicated by a particular measure, is the one with the smallest forecast value of that measure. For each period, we rank the forecasting ability of the six models by ranking the magnitudes of the forecast errors.

RESULTS

Six estimation models are used in this study, namely, RW, OLS, GARCH (1,1), ARCH (1,1)-M, TARCH (1,1) and EGARCH (1,1) models. These models are estimated for each of the five ASEAN markets for the pre-crisis, crisis and post-crisis periods. These estimated models are then used for forecasting the values of the market index for the last 20 days of each period of an ASEAN market. The four statistical measures of forecast error—RMSE, MAE, MAPE and Theil—are computed for each forecast. The results of the RMSE and their resultant rankings for these six models are given in Table 1. The other three measures of forecast errors are not reported here as they provide the same rankings as those based on the RMSE.

For the five ASEAN equity markets, the magnitudes of the forecast errors are the least in the pre-crisis period and the greatest in the crisis period. In the pre-crisis period, the

RMSE values range from 0.013 to 0.060. They are the lowest (0.013 to 0.016) for Singapore and the highest (0.053 to 0.060) for Thailand. The forecasting ability of the models is rather poor in the crisis period. The forecast errors in each ASEAN market are very much higher during this period of high volatility. They range widely from 0.047 to 0.436. The forecast errors are the lowest (0.047 to 0.058) for the Philippines. Rather surprisingly, contrary to the results in the pre-crisis period, the RMSE values for Malaysia are exceptionally high (0.376 to 0.436). Thus, the forecasting performance of the models for Malaysia during the crisis period has deteriorated. The forecasting ability of the models improves in the post-crisis period and, generally, reverts to that during the pre-crisis period. As in the pre-crisis period, the forecasting performance is the best for Malaysia and the worst for Thailand.

From the rankings of the models in Table 1, no one single model is the best for these ASEAN markets. In the pre-crisis period, the TARCH model is the best forecast model for Malaysia. The OLS model is the best for Singapore and the Philippines, while the ARCH-M model is the best for Thailand and Indonesia. In the crisis period, the best forecast model for Malaysia, Singapore and the Philippines is the ARCH-M model, while for Thailand and Indonesia it is the RW model. In the post-crisis period, the TARCH and EGARCH models, which capture the asymmetrical market returns volatility, are the best forecast models. The TARCH model is the best for Malaysia and Thailand, while the EGARCH model is the best for the other three ASEAN markets. Thus, our findings show that the best forecast model for an ASEAN market is different for each period except for Malaysia, where the TARCH model is the best in both the pre-crisis and post-crisis periods.

The estimated models for the ASEAN markets are given in Table 2. The F-statistics in Panel A for the pre-crisis period show that the models are significant in all countries except Singapore. The current returns are positively correlated with the previous-day returns and, again, the correlation is significant except for Singapore. The results of the LM test for the presence of ARCH effects show that the OLS model used for Singapore and the Philippines is inadequate. However, the LM test results are not significant for the different variants of the GARCH model used for Malaysia, Thailand and Indonesia. The ε_{t-1}^2 and σ_{t-1}^2 terms in the TARCH model for Malaysia and in the ARCH-M model for Thailand and Indonesia are significant, thereby highlighting the salient features of the time-varying volatility of stock returns in these countries. The $\varepsilon_{t-1}^2 \xi_{t-1}$ term in the TARCH model for Malaysia is significant, thereby indicating evidence of asymmetrical impact of good/bad news on stock returns in the Malaysian equity market. The risk-returns trade-off of the ARCH-M model is not significant for both Thailand and Indonesia.

In the crisis period, the F-statistics in Panel B show that the models are significant for Singapore and the Philippines but not for Malaysia. The current returns are again positively correlated with the previous-day returns and the correlations are significant for these three markets. The results of the LM test show the presence of ARCH effects in the RW model for Thailand and Indonesia but not in the ARCH-M model for the other three ASEAN countries. Similarly, the time-varying returns volatility is highlighted by the significance of ε_{t-1}^2 and σ_{t-1}^2 terms in the ARCH-M model for these three equity markets. Likewise, the risk-returns trade-off of the ARCH-M model is not significant in these three markets.

Table 1. Measures of Forecast Errors (RMSE) and Rankings of the Six Models for the ASEAN Equity Markets

	Pre-crisis period	Crisis period	Post-crisis period
Malaysia			
RW	0.014245 [2]	0.408740 [2]	0.031455 [5]
OLS	0.014251 [3]	0.436140 [3]	0.031210 [3]
GARCH	0.014939 [4]	0.425105 [6]	0.031845 [6]
ARCH-M	0.015229 [5]	0.375777 [1]	0.031356 [4]
TARCH	0.013663 [1]	0.431205 [5]	0.029569 [1]
EGARCH	0.015609 [6]	0.429204 [4]	0.030358 [2]
Singapore			
RW	0.012963 [2]	0.106123 [3]	0.064606 [4]
OLS	0.012919 [1]	0.108732 [4]	0.064913 [5]
GARCH	0.014035 [3]	0.106031 [2]	0.063592 [3]
ARCH-M	0.016377 [6]	0.081392 [1]	0.069123 [6]
TARCH	0.014864 [5]	0.115940 [5]	0.061608 [2]
EGARCH	0.014354 [4]	0.117417 [6]	0.061485 [1]
Thailand			
RW	0.056169 [2]	0.147977 [1]	0.067151 [5]
OLS	0.058650 [4]	0.150816 [2]	0.066169 [2]
GARCH	0.056265 [3]	0.166925 [5]	0.067020 [4]
ARCH-M	0.053447 [1]	0.157569 [3]	0.067016 [3]
TARCH	0.059201 [5]	0.168850 [6]	0.065691 [1]
EGARCH	0.059936 [6]	0.162520 [4]	0.067353 [6]
Indonesia			
RW	0.034466 [6]	0.122294 [1]	0.059472 [5]
OLS	0.029054 [3]	0.125098 [2]	0.059809 [6]
GARCH	0.030288 [4]	0.140339 [6]	0.056914 [3]
ARCH-M	0.027682 [1]	0.137391 [5]	0.059238 [4]
TARCH	0.030344 [5]	0.125668 [3]	0.056887 [2]
EGARCH	0.028086 [2]	0.129730 [4]	0.054717 [1]
Philippines			
RW	0.032303 [2]	0.053314 [4]	0.035968 [4]
OLS	0.031874 [1]	0.052923 [3]	0.038613 [6]
GARCH	0.033983 [3]	0.049697 [2]	0.035044 [3]
ARCH-M	0.035247 [4]	0.046533 [1]	0.038056 [5]
TARCH	0.035821 [5]	0.054867 [5]	0.031570 [2]
EGARCH	0.037067 [6]	0.057748 [6]	0.031020 [1]

The numbers in [ ] indicate rankings of the models in each period for each equity market, [1] having the lowest RMSE.

Table 2. The Best Estimated Models for the Five ASEAN Equity Markets in the Pre-crisis, Crisis and Post-crisis Periods

		Malaysia	Singapore	Thailand	Indonesia	Philippines
Panel A. Pre-crisis Period						
Model		TARCH	OLS	ARCH-M	ARCH-M	OLS
Mean Equation	c	0.0005	0.0002	–0.0003	–0.0006	0.0006
	r_{t-1}	0.2000**	0.0292	0.1708**	0.3493**	0.2016**
	σ_t			0.0562	0.1419	
Variance Equation	c	0.0000**		0.0000**	0.0000**	
	ε^2_{t-1}	0.0612**		0.1282**	0.3760**	
	$\varepsilon^2_{t-1}\xi_{t-1}$	0.0405**				
	σ^2_{t-1}	0.8973**		0.8345**	0.2609**	
F-statistic (p-value)		0.000	0.301	0.020	0.000	0.000
ARCH-LM (p-value)	5 lags	0.420	0.000	0.306	0.973	0.000
	10 lags	0.713	0.000	0.047	0.883	0.000
Panel B. Crisis Period						
Model		ARCH-M	ARCH-M	RW	RW	ARCH-M
Mean Equation	c	–0.0024	–0.0038*	–0.0034*	–0.0019	–0.0031
	r_{t-1}	0.2335**	0.1873**			0.2030**
	σ_t	0.0546	0.2031			0.1003
Variance Equation	c	0.0000	0.0000**			0.0000*
	ε^2_{t-1}	0.2324**	0.1950**			0.2222**
	σ^2_{t-1}	0.8170**	0.7982**			0.7976**
F-statistic (p-value)		0.319	0.003			0.000
ARCH-LM (p-value)	5 lags	0.503	0.650	0.000	0.000	0.987
	10 lags	0.870	0.814	0.000	0.000	0.981

Table 2 (continued)

		Malaysia	Singapore	Thailand	Indonesia	Philippines
Panel C. Post-crisis Period						
Model		TARCH	EGARCH	TARCH	EGARCH	EGARCH
Mean Equation	c	0.0005	0.0001	0.0004	0.0001	–0.0006
	r_{t-1}	0.1957**	0.0497	0.0449	0.1717**	0.1372**
	σ_t					
Variance Equation	c	0.0000**	–0.5140*	0.0000**	–2.4404**	–0.7208**
	ε^2_{t-1}	0.1046**		0.1375**		
	$\varepsilon^2_{t-1}\xi_{t-1}$	0.0753*		0.0347		
	σ^2_{t-1}	0.7987**		0.7620**		
	$\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$		0.1969**		0.5262**	0.1964**
	$\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$		–0.0343		0.0133	–0.0465**
	$\ln \sigma_{t-1}$		0.9580**		0.7509**	0.9299**
F-statistic (p-value)		0.009	0.717	0.407	0.000	0.002
ARCH-LM (p-value)	5 lags	0.962	0.426	0.976	0.992	0.992
	10 lags	0.889	0.737	0.999	0.953	0.999

* Significant at 5% level. ** Significant at 1% level. The significance test is based on the Newey-West's (1987) heteroscedasticity consistent standard errors for the OLS model and the quasi-maximum likelihood standard errors due to Bollerslev and Wooldridge (1992) for the other models. The F-statistic is for testing the significance of the model. ARCH-LM refers to the Engle (1982) LM test for the presence of ARCH effects.

In the post-crisis period, where the best models are TARCH and EGARCH, the F-statistics in Panel C are significant for Malaysia, Indonesia and the Philippines but not for the other two ASEAN markets. Similarly, the correlation between the current returns and the previous-day returns is significantly positive for the same three ASEAN markets. The non-significance results of the LM test show that the TARCH and EGARCH models fully account for the ARCH effects. The presence of the time-varying returns volatility in Malaysia and Thailand is indicated by the significance of the ε^2_{t-1} and σ^2_{t-1} terms in the TARCH models. The $\varepsilon^2_{t-1}\,\xi_{t-1}$ term confirms significant asymmetric returns in Malaysia but not in Thailand. The $\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert$ and ln (σ^2_{t-1}) terms in the EGARCH model are significant for Singapore, Indonesia and the Philippines. But the $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ term is only significant for the Philippines, thereby indicating asymmetric returns in this country only.

CONCLUSION

This study examines six models for forecasting the values of the leading market indices of five ASEAN equity markets in the pre-crisis, crisis and post-crisis periods. The forecasts are the most reliable in the pre-crisis period and the poorest in the crisis period. The forecast ability of the models in the post-crisis period reverts to that in the pre-crisis period.

No one single forecast model is found to be the best for these ASEAN equity markets. Instead three models, TARCH, OLS and ARCH-M, are found to be the best for the ASEAN markets in the pre-crisis period. In the crisis period, the best models found are ARCH-M and RW, while in the post-crisis period the best models are TARCH and EGARCH, which capture the asymmetric volatility in the market returns.

In the pre-crisis period, the results of the best estimated models show that the models are significant with positive relationship between the current returns and the previous-day returns except for Singapore. The TARCH and ARCH-M models are adequate in capturing the time-varying returns volatility and the asymmetric return volatility, while the OLS model is inadequate for this purpose. In the crisis period, the best models—ARCH-M and RW—are significant except for Malaysia. The current returns and the previous-day returns have a significantly positive relationship. The varying returns volatility is adequately captured in the ARCH-M model but not in the RW model. Finally, in the post-crisis period, the best models, TARCH and EGARCH, are significant for only three of the five ASEAN markets. Similarly, the relationship between the current returns and the previous-day returns is significantly positive for the same three equity markets. These models not only adequately captured the varying returns volatility in the five markets but also the asymmetric returns in Malaysia and the Philippines. The risk-returns trade-off is not significant in the markets in the pre-crisis and crisis periods modelled by the ARCH-M model.

In a way, the findings from this study testify that the best forecasting model is related to the market conditions, and also possibly to the different stages of development of the markets. For any market, no one single model should be used to forecast future stock returns. In order to be as accurate as possible, albeit within the limitations of empirical studies, one has to work out the best forecasting model for a particular market and in accordance to the prevailing market conditions.

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