The current issue and full text archive of this journal is available at
www.emeraldinsight.com/1526-5943.htm

Long memory properties and asymmetric effects of emerging equity market

Evidence from Malaysia

Turkhan Ali Abdul Manap and Salina H. Kassim
Department of Economics, International Islamic University Malaysia, Kuala Lumpur, Malaysia

Abstract

Purpose – The purpose of this paper is to examine the long memory property of equity returns and volatility of emerging equity market by focusing on the Malaysian equity market, namely the Kuala Lumpur Stock Exchange (KLSE).

Design/methodology/approach – The study adopts the Fractionally Integrated GARCH (FIGARCH) model and Fractionally Integrated Asymmetric Power ARCH (FIAPARCH), focusing on the Malaysian data covering the period from April 15, 2004 to April 30, 2007.

Findings – The study finds evidence of long memory property as well as asymmetric effects in the volatility of the KLSE. The traditional ARCH/GARCH is shown to be insufficient in modeling the volatility persistence. The FIAPARCH specification outperforms the FIGARCH model by capturing both asymmetry effects and long memory in the conditional variance.

Research limitations/implications – The results of this study have practical implications for the investors intending to invest in the emerging markets such as Malaysia. Understanding volatility and developing the appropriate models are important since volatility can be a measure of risk which is highly relevant in forecasting the conditional volatility of returns for portfolio selection, asset pricing, and value at risk, option pricing and hedging strategies.

Originality/value – This study contributes in providing the empirical evidence on the long memory property of equity returns and volatility of an emerging equity market with reliable estimation models, which is currently lacking, particularly for emerging markets.

Keywords Malaysia, Emerging markets, Equity capital, Stock returns, Stock exchanges, Long memory process, Fractionally Integrated Asymmetric Power ARCH, Stock market volatility

Paper type Research paper

1. Introduction

The presence of long-memory components in stock returns has important implications for many of the financial economics paradigms. If stock returns display long-term dependence, then they exhibit significant autocorrelation between the observations that are widely separated in time. Since the series realizations are not independent over time, realizations from the remote past can help to predict future returns, hence giving rise to the possibility of consistent speculative profits. This is in contrast to the "martingale"

The authors are grateful to an anonymous referee and the Editor of this journal for their constructive comments on an earlier version of this paper. The authors acknowledge the financial support from Research Management Center, International Islamic University Malaysia (Grant No: EDW-A07-138).

The Journal of Risk Finance
Vol. 12 No. 5, 2011
pp. 356-370

1526-5943
DOI 10.1108/15265941111176109

or random walk-type behavior that many theoretical financial asset-pricing models usually assume. The presence of long memory in asset returns contradicts the weak-form market efficiency hypothesis which states that conditioning on past returns, future asset returns are unpredictable. Therefore, optimal consumption or savings portfolio decisions may become sensitive to the investment horizon. The existence of long-memory properties in asset returns calls into question the reliability of linear modeling and invites the development of non-linear pricing models at the theoretical level to account for the long-memory behavior. Mandelbrot (1971) observes that in the presence of long memory, the arrival of new market information cannot be fully arbitraged away and martingale models of asset prices cannot be obtained from arbitrage. As a result, Yajima (1985) concludes that if the underlying continuous stochastic processes of asset returns exhibit long memory, then the pricing derivatives by martingale models as well as the statistical inference concerning asset-pricing models based on standard testing procedures may not be appropriate.

Owing to the theoretical and practical importance of this issue, extensive studies are conducted on analyzing the long-memory properties of financial asset returns particularly in major financial markets. Greene and Fielitz (1977) use the R/S statistic of Hurst (1951) to test for the long-term dependence in the daily returns of 200 individual stocks on the New York Stock Exchange from December 23, 1963 to November 29, 1968 and report evidence of persistence of the stock prices under review. Aydogan and Booth (1988) also use the original R/S statistics to test for the long-memory property in common stock returns. Lo (1991) uses a modified version of the R/S statistic which controls the possible short-term dependencies in the data and find no evidence in favor of long memory of the monthly and daily returns on Center for Research in Security Prices stock indexes. In contrast, Ding *et al.* (1993) examine the long-memory properties of several transformation of the absolute value of daily returns on the Standard & Poor's (S&P) 500 and obtain considerable evidence of long memory in the squared and absolute returns. Crato (1994) uses the exact maximum likelihood method of Sowell (1992) and finds no evidence of long memory for the stock return series of the G-7 countries. By using both the modified R/S method of Lo (1991) and the Geweke and Porter-Hudak (GPH) (1983) method, Cheung and Lai (1995) find no evidence of persistence in several international stock return series. Lobato and Savin (1998) test the presence of long memory in daily and squared returns on S&P 500 series by using semi-parametric procedures. Their test results indicate no evidence of long memory in the levels of daily returns but find existence of long memory in the absolute and squared returns.

Despite the extensive literature on the long-memory properties of stock markets prices in the developed countries, little has been done on the time series properties of emerging markets asset prices. As pointed out by Harvey (1995) and Kilic (2004), compared to the developed markets, the emerging capital markets (ECMs) such as that of Latin America, Asia, the Middle East and Africa, exhibit higher expected returns and volatility. Owing to the low correlation with the developed countries' stock markets, the unconditional portfolio risk of a global investor could be significantly reduced by investing in the ECMs. The ECMs have attracted the attention from investors and investment funds seeking to further diversify their portfolios as these markets provide a new menu of opportunities for the investors. As these markets provide potential diversification benefits to the investors, a complete characterization and understanding of the dynamic behavior of the stock returns in the ECMs is warranted. The ECMs are likely to exhibit characteristics different from those observed in the developed capital markets. Barkoulas *et al.* (2000) analyze the long-memory properties of weekly Greek stock market data and obtain strong evidence of long memory in the conditional mean process, a finding contrary to the results from the developed stock markets. One may expect biases due to market thinness and non-synchronous trading that is possibly more severe in the ECMs. Moreover, in contrast to the developed capital markets which are highly efficient in terms of the speed of information transmission, investors in the ECMs may tend to react slowly and gradually to new information. All this may lead one to expect the ECMs stock returns to behave differently and have distinct properties compared to those of the developed capital markets.

In the light of the above, this paper attempts to analyze the long-memory properties of an ECM, namely, the Kuala Lumpur Stock Exchange (KLSE). This paper hopes to contribute by enriching the literature on the assessment of the long-memory property of the emerging equity market, which is relatively scarce at the moment. The rest of the paper is organized as follows. Section 2 discusses the methodology to study the long-memory properties of stock market prices which includes the concept, estimation and testing procedures. Section 3 describes the data preliminary, followed by Section 4 which reports the findings. Finally, Section 5 concludes.

2. Methodology

The presence of long-memory property or long-term dependence in a time series can be defined in terms of the persistence of autocorrelations. In simple terms, long memory in time series implies that there exist dependencies between distant observations. In contrast, if correlations among observations become negligible at long lags, then the series is said to exhibit short memory. The simplest method to investigate the memory property of time series is by relying on the autocorrelation function (ACF) in which, for the case of long memory, the ACF decays hyperbolically and eventually dies out. The ACF for an I(0) process shows an exponential decay, while for an I(1) process, it shows an infinite persistence.

Another approach to assess the existence of the long-memory property is through the R/S statistics proposed by Hurst (1951) and later revised by Lo (1991). However, the estimation method of Geweke and Porter-Hudak (1983) perhaps, has been the most often used in financial research due to its ease of implementation. A major strength of the GPH test is that it does not depend on any assumption about the underlying distribution of the stock prices. However, an important drawback of the test is that it only indicates whether there is statistically significant long-memory property in the data, but does not provide any measure for the long memory itself. If statistically significant long memory is detected in a series, it would also be of interest to estimate a full parametric model for the data.

Therefore, a more appealing approach to detect potential long memory is perhaps to estimate a long-memory model and test the statistical significance of the long-memory parameter directly. This estimate of the long-memory parameter could then be used for other purposes such as to see whether the detected long memory could be used for more accurate forecasting. For this purpose, the most commonly used model is the ARFIMA-FIGARCH model. The ARFIMA essentially analyses the conditional mean of the time series, while the fractionally integrated generalized autoregressive conditional heteroscedastic (FIGARCH) focuses on the conditional variances. In the context of this study, the FIGARCH is more relevant due to the following:

- since the data used represent index returns at daily intervals, it is possible to have "stable" returns due to the components of index are not traded at the same time; and
- the degree of predictability of the mean is marginal and has minor consequence for the conditional variance.

In the following discussion, we summarize the idea behind the GARCH and FIGARCH models, which is the method adopted in this study.

More formally, consider the univariate process for the stock returns, r_t, as follows:

$$r_t = \mu_t + \varepsilon_t \tag{1}$$

Engle (1982) defined an ARCH process, all ε_t of the form:

$$\varepsilon_t = z_t \sigma_t \tag{2}$$

where z_t is an independently and identically distributed process with $E(z_t) = 0$ and $var(z_t) = 1$. By definition, ε_t is serially uncorrelated with a mean equal to 0, but its conditional variance σ_t is measured with respect to time $t-1$ information set. The conditional variance of ARCH (q) can be expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha(L)\varepsilon_t^2 \tag{3}$$

where $\alpha_0 > 0$, $\alpha(L) = \sum_{i=1}^{p} L^i \varepsilon_t^2$ with $\alpha_i \geq 0$ for all i. The ARCH model is used to describe volatility clustering. The conditional variance of ε_t is indeed an increasing function of the squared of the shock that occurred in $t-1$. Consequently, ε_t was large in absolute value, and σ_t^2 thus ε_t is expected to be large (in absolute value) as well. Owing to the empirical evidence that a high ARCH order has to be selected to assess the dynamics of the conditional variance, there is a cost involved in estimating more parameters. Bollerslev (1986) later extends the ARCH model to GARCH, which can be expressed as follows:

$$\sigma_t^2 = \alpha_0 + \alpha(L)\varepsilon_t + \beta(L)\sigma_t^2 \tag{4}$$

where $\beta(L) \equiv \sum_{j=1}^{q} L^j$ with $\beta_j \geq 0$ for all j. We could rearrange equation (4) as:

$$[\alpha_0 - \alpha(L) - \beta(L)]\varepsilon_t^2 = \alpha_0 + [1 - \beta(L)]\left(\varepsilon_t^2 - \sigma_t^2\right) \tag{5}$$

To ensure conditional variance to be non-negative, it is assumed that all the roots of the polynomial $[1 - \beta(L)]$ lie outside the unit circle. The $GARCH(p,q)$ model is covariance stationary if all the roots of $1 - \alpha(L) + \beta(L)$ lie outside the unit circle. To take into account of a unit root in the autoregressive polynomial $[\alpha_0 - \alpha(L) - \beta(L)]$, Engle and Bollerslev (1986) introduced the IGARCH model which is expressed as:

$$\phi(L)(1 - L)\varepsilon_t^2 = \alpha + [1 - \beta(L)]\left(\varepsilon_t^2 - \sigma_t^2\right) \tag{6}$$

where $\phi(L) = [1 - \alpha(L) - \beta(L)](1 - L)^{-1}$. In IGARCH process, current information remains of importance when forecasting the volatility for all horizons.

The GARCH or IGARCH models are able to describe certain properties of economics time series, such as volatility clustering and excess kurtosis[1].

However, several recent studies have reported the existence of long memory in the autocorrelations of some power of absolute returns. These studies find that even if the GARCH specification is able to explain the short-run pattern of volatility, it fails to match the long-run volatility persistence. Motivated by this evidence of a long-memory component in volatility, Baillie *et al.*(1996) (BBM model) proposed the FIGARCH model by replacing the first difference operator of equation (6) with the fractional difference operator $(1-L)^d$ as follows:

$$\phi(L)(1-L)^d\varepsilon_t^2 = \alpha_0 + [1-\beta(L)]\left(\varepsilon_t^2 - \sigma_t^2\right) \tag{7}$$

where the parameter d is allowed to be any real number between 0 and 1. Rearranging the terms in equation (7), an alternative representation for the *FIGARCH*(p, d, q) model can be obtained as:

$$\sigma_t^2 = \alpha_0[1-\beta(L)]^{-1} + [1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d]\varepsilon_t^2 \tag{8}$$

All the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit circle. Persistence of shocks to the conditional variance, or the degree of the long-term dependencies is measured by the parameter d. The FIGARCH process nests the GARCH process for $d = 0$ and IGARCH process for $d = 1$ as special cases. The cumulative impulse response weights are given by the coefficients in the lag polynomial, $\lambda(L)$:

$$\lambda(L) = 1 - [1-\beta(L)]^{-1}\phi(L)(1-L)^d \tag{9}$$

The fractional differencing operator, $(1-L)^d$, has a binomial expansion which is most conveniently expressed in terms of the hypergeometric function as follows:

$$(1-L)^d = F(-d,1;1;L) = \sum_{k=0}^{\infty}\frac{\Gamma(k-d)}{\Gamma(k+1)\Gamma(-d)}L^k \tag{10}$$

This process is not covariance stationary but it is strictly stationary and ergodic for d be any real number between 0 and 1 (Bollerslev and Mikkelsen, 1996).

On the other hand, empirical works in modeling the conditional volatility of stock prices has found that the stock volatility responds asymmetrically to positive versus negative shocks (Engle and Ng, 1993). This suggests that stock returns are negatively correlated with changes in return volatility, i.e. volatility tends to rise in response to "bad news" (lower returns than expected) and to fall in response to "good news" (higher returns than expected). Nelson (1991) was the first to formally model this potential asymmetry, followed by several extensions of such model. However, the model introduced by Ding *et al.* (1993) which is known as the asymmetric power ARCH (APARCH) couples the flexibility of a varying component with asymmetry coefficient and is shown to nest at least seven other ARCH extensions as special cases. The APARCH (p, q) model can be expressed as follows:

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{q}(\alpha_i|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^\delta + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^\delta \tag{11}$$

where $\delta > 0$ and $-1 < \gamma_i < 1 \quad (i = 1, 2, \ldots, q)$. Asymmetric or leverage effect in this model is captured by the γ_i term. For an *APARCH* (model, when $\gamma > 0$, negative shocks lead to higher volatility, vice versa. An *APARCH*(p, q) model of asymmetric differs from other *GARCH* type volatility models with the introduction of the power term, δ, which is to be estimated. The introduction and estimation of the power term is an attempt to account for the true distribution underlying volatility. The idea behind the introduction of a power term arose from the fact that in modeling financial data, the assumption of normality, which restricts δ to either 1 or 2, is often unrealistic due to significant skewness and kurtosis. Allowing δ taking the form of a free parameter to be estimated removes this arbitrary restriction.

Tse (1998) proposed the fractionally integrated APARCH (FIAPARCH) model, which extended the FIGARCH model by adding the function $(|\varepsilon_i| - \gamma_i\varepsilon_t)^\delta$ of the APARCH model to capture the asymmetry and the long-memory properties in the conditional variance. The FIAPARCH can be expressed as:

$$\sigma_t^\delta = \alpha_0 - [1 - \beta(L)]^{-1} + [1 - \phi(L)[1 - \beta(L)]^{-1}(1 - L)^d](|\varepsilon_i| - \gamma_i\varepsilon_t)^\delta \qquad (12)$$

where δ, λ, and γ are the parameters of the model. The FIAPARCH model can capture some well-known stylized fact of volatility:

- for $0 < d < 1$, volatility displays the long-memory property;
- when $\gamma > 0$, negative shocks give rise to higher volatility than positive shocks, vice versa;
- the power term δ of returns for the predictable structure in the volatility pattern should be determined by the data; and
- the FIAPARCH model also nests the FIGARCH model when $\delta = 2$ and $\gamma = 0$.

Thus, the FIAPARCH model is superior to the FIGARCH model because it can capture asymmetry and long memory in the conditional variance (Tse, 1998).

In order to test for the presence of asymmetric response of volatility to negative shocks, the Engle and Ng (1993) diagnostic tests for asymmetry in volatility are conducted. Engle and Ng designed three tests to determine possible misspecification of the conditional variance equation. These tests are called sign bias test (SBT), negative SBT (NSBT) and positive SBT (PSBT). The SBT detects whether positive and negative return shocks of the same magnitude produce the same amount of volatility; the NSBT examines whether negative return shocks of different magnitude (size, like large, and small) have different impact on volatility; while the PSBT focuses on the different effects that large and small positive return shocks have on volatility. For this purpose, an indicator dummy variable S_{t-1}^- is defined to take the value of 1 if $\hat{\varepsilon}_{t-1} < 0$ and 0 otherwise (and $S_{t-1}^+ \equiv 1 - S_{t-1}^-$). Engle and Ng (1993) propose to run the following regressions:

$$\varepsilon_t^2 = \alpha + \alpha_1 S_{t-1}^- + e_t \qquad (13)$$

$$\varepsilon_t^2 = \beta + \beta_1 S_{t-1}^- \varepsilon_{t-1} + e_t \qquad (14)$$

$$\varepsilon_t^2 = \gamma + \gamma_1 S_{t-1}^+ \varepsilon_{t-1} + e_t \qquad (15)$$

and test the significance of α_1, β_1, and γ_1 through a t-test. A joint test for sign and size bias (JTSB) based on the regression is also proposed as follows:

$$\varepsilon_t^2 = \alpha + \beta_1 S_{t-1}^- + \beta_2 S_{t-1}^- \varepsilon_{t-1} + \beta_3 S_{t-1}^+ \varepsilon_{t-1} + e_t \quad (16)$$

where the null hypothesis that the volatility model used is correct holds when $\beta_1 = \beta_2 = \beta_3 = 0$. The t-ratios of these three coefficients are test statistics for the three types of bias. A joint test statistic is defined in Lagrange Multiplier fashion as equal to nR^2 from equation (16). It follows a χ^2 distribution with three degrees of freedom.

We estimate all the models using the quasi-maximum likelihood estimation (QMLE) method as implemented by Laurent and Peters (2002) in Ox. To obtain robust inference about the estimated models, we compute the robust standard errors as suggested by Bollerslev and Wooldridge (1992)[2]. Since the distribution of the Kuala Lumpur Composite Index (KLCI) return series are far from normal as indicated in the preliminary analysis in the next section, all the estimations are based on the student-t distribution.

3. Data preliminary

The study uses the daily KLCI which is the benchmark index for the Malaysian stock market – the KLSE. A total of 3,464 data observations is being considered, covering the period from April 15, 2004 to April 30, 2007. Following the standard practice, the stock returns are defined as $r_t = (p_t - p_{t-1})*100$, where p_t is the log of the index at time t. Figure 1 shows the graphs of the daily KLCI returns, absolute returns and squared returns over the sample period. It can be observed from the graphs that relatively volatile periods, characterized by large price changes, alternate with more tranquil periods in which the index remains more or less stable. This indicates that large index returns (both positive and negative) seem to occur in clusters and so does volatility. The volatility clustering phenomenon which is typical of asset prices and exchange rates seems to occur in the KLSE as well.

Summary statistics for the index returns are given in Table I. The table indicates that daily returns have small positive means and medians over the sample period. One of the usual ways of getting an idea on the distribution of a time series is to look at the kurtosis and skewness and compare them with that of a normal random variable. The last two rows of Table I indicate that the kurtosis of the daily returns is much larger than that of a normal random variable. This reflects the fact that the tails of the distribution of index returns are fatter than the tails of the normal distribution, which in turn means that large observations occur more often than one might expect for a normally distributed variable.

Since any symmetric distribution have skewness equal to 0, Table I indicates that the distribution of daily index returns is asymmetric. The positive value of skewness indicates that for the KLSE stock returns, the right tail of the distribution is fatter than the left tail, or large positive returns tend to occur more often than large negative ones. Again, this observation indicates that daily KLCI stock return distribution is far from being normal.

To gain some insights into the dependence structure of the series, Figure 2 shows the first 200 autocorrelations for the daily stock index, index returns, absolute returns and squared returns together with two-sided 5 percent critical values ($\pm 1.92\mathrm{T}^{-1/2}$ where T is the sample size). The asymptotic critical values are not strictly valid for a process with ARCH effects, still they may be considered to be useful as guidelines. It is clear from the figure that the KLCI log index has autocorrelations close to unity at all selected lags and, hence, it seems to mimic the correlation properties of a random walk process.

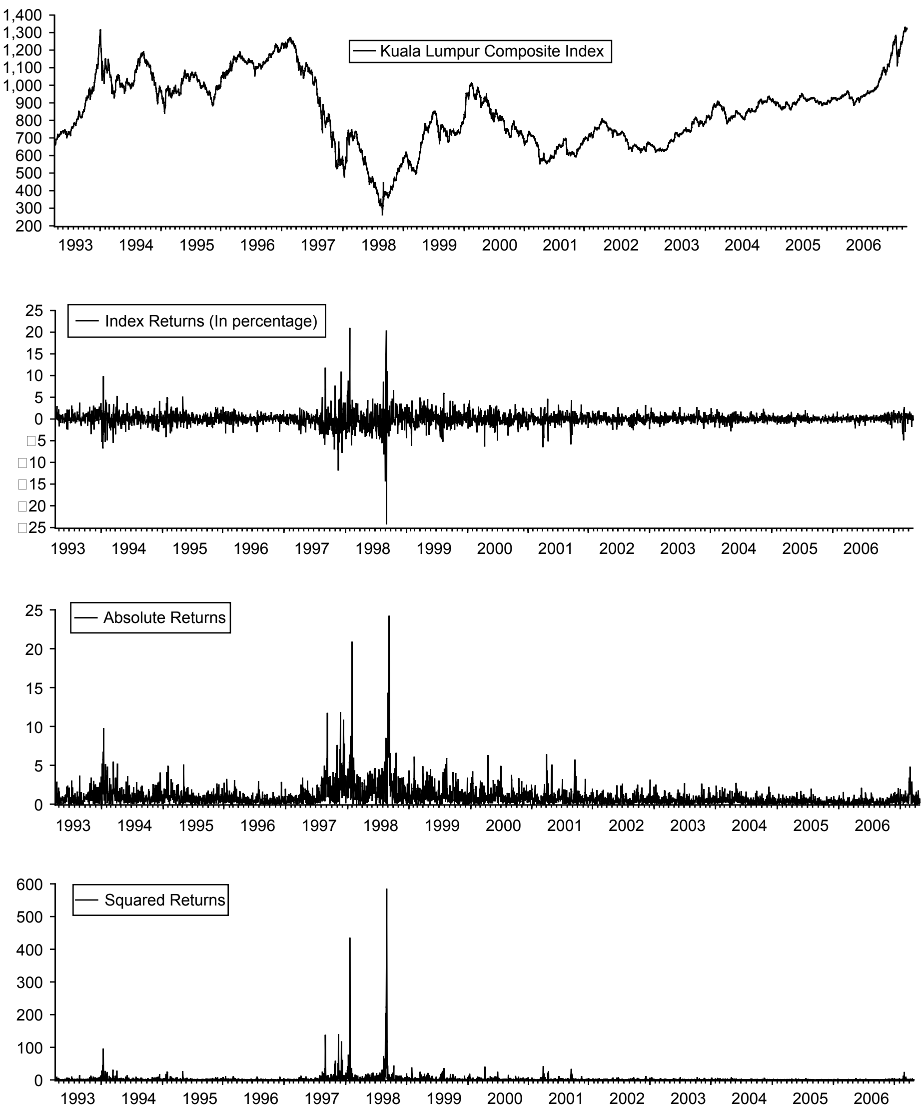

Figure 1.
KLCI index, index returns, absolute returns and squared returns

There is a small, positive but significant first-order autocorrelation in the stock index returns, while higher orders are not significant at conventional levels. On the other hand, for the absolute returns and squared returns, the autocorrelations start-off at a moderate level (about 0.42) but remain significantly positive for a substantial number of lags.

Moreover, autocorrelation in the absolute returns is generally somewhat higher than the autocorrelation in the squared returns. This illustrates what has become known as the "Taylor property" (Taylor, 1986), that is, when calculating the autocorrelations for the series R^{δ} for various values of δ, one almost invariably finds that autocorrelations are the largest for $\delta = 1$.

As evident in Figure 2, autocorrelations for the absolute returns are not only larger than those of squared returns, but also more persistent in the sense that they decay much more slowly. The autocorrelations in absolute and squared returns seem to mimic the correlation properties of a long-memory processes rather than a short-memory stationary process for which autocorrelations decay to zero at an exponential rate. In addition, the very slow decay of the autocorrelations in absolute and square returns indicates that linear association between distant observations is somewhat persistent and autocorrelations decay at a hyperbolic rate. This describes the behavior

Table I.
Summary statistics of KLCI

	Series returns
Mean	0.020
Median	0.026
Maximum	20.817
Minimum	−24.153
Variance	1.592
Skewness	0.508
Kurtosis	43.857

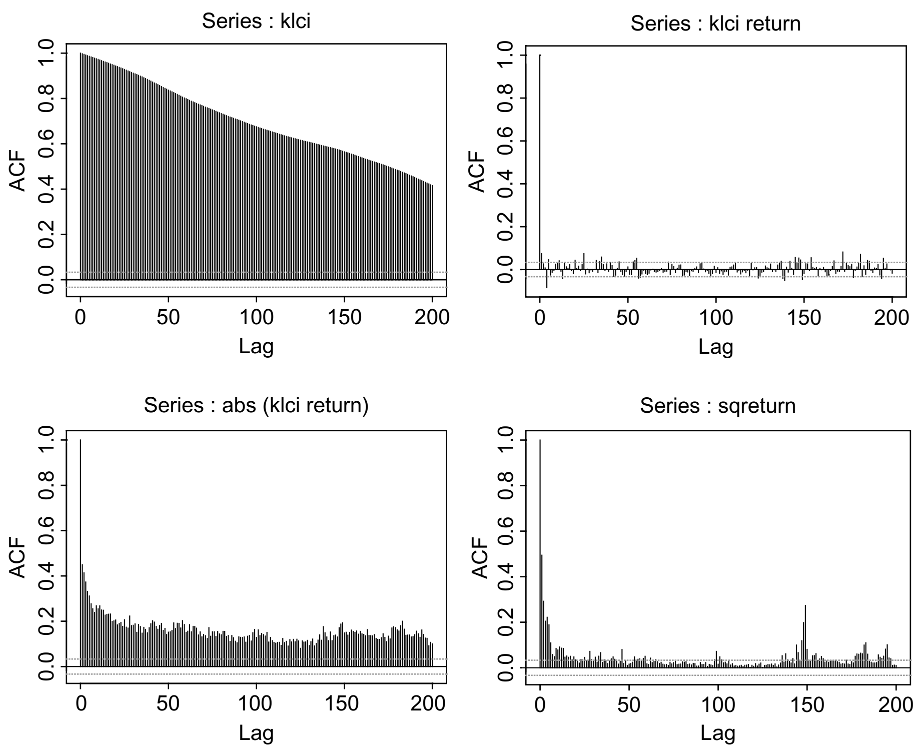

Figure 2.
ACF of daily index, return and absolute return of KLCI

of autocorrelations in absolute and squared returns are consistent with the time series models with long-memory or long-range dependence. These descriptions about the characteristics of autocorrelations in the KLCI, index returns, absolute and squared returns are in conformity with the findings from developed stock markets (Ding *et al.*, 1993). We also present the modified R/S test and GPH test results for the KLCI returns and its absolute returns in Table II. Both tests indicate that absolute returns have stronger long-range dependence, which is in conformity with our autocorrelation observations. In this paper, the first-order version of the aforementioned process is considered, namely *GARCH*(1, 1), *IGARCH*(1, 1), *APARCH*(1, 1), *FIGARCH*(1, 1) and *FIAPARCH*(1, 1).

4. Empirical results

In light of the discussion in the previous section, and given that the data used represent index returns at daily intervals, it is possible to have "stable" returns due to the components of the index that are not traded at the same time. The degree of predictability of the mean is marginal and has minor consequences for the conditional variance. In this study, our focus is to model the conditional variance rather than the conditional mean. Therefore, conditional variance of the KLCI index returns are modeled by the FIAGARCH process which allows one to consider persistence in the autocorrelations of index returns as well as volatility clustering phenomenon.

We begin by using the first development in this area, the GARCH model. We then proceed to an elaborated model designed to test for the existence of a unit root in the second moment, the FIGARCH model. These models would enable us to come up with more conclusive findings. Following most of the empirical studies, we estimate our benchmark model of GARCH (1, 1). The estimation result for the GARCH (1, 1) model is presented in column 1 of Table III[3]. It shows that all of the coefficients concerning the GARCH parameters are highly significant. We also estimate GARCH (1, 2) and GARCH (2, 1) models, but it turns out that the additional coefficient in the GARCH (1, 2) model is insignificant even at 10 percent level and the additional coefficient in the GARCH (2, 1) model is negative. Indeed, most applied works have frequently demonstrate that the GARCH (1, 1) model is able to represent a majority financial time series, as in the case of this study.

Another interesting fact that is apparent from a visual inspection of our GARCH model is that the sum of α_1 and β_1 is more than unity, which is suggestive of IGARCH. So we proceed to test IGARCH model where we impose the restriction of $\alpha_1 + \beta_1 = 1$. The estimates for the restricted IGARCH (1, 1) model in the second column of the table are very similar to the results for the GARCH (1, 1) model. The estimated maximum value of the likelihood function is identical, indicating that there is no significant difference between these two models. According to the values of the Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, there is no statistically significant evidence of misspecification. However, the Engle and Ng

Test	KLCI returns	KLCI absolute returns
Modified R/S	1.8694*	4.1015**
GPH	2.0928*	4.1193**

Table II. Modified R/S and GPH test results for KLCI

Table III.
GARCH type model estimation results for daily KLCI index returns

	Model 1	Model 2	Model 3	Model 4	Model 5
μ	0.034 (0.014)**	0.034 (0.014)**	0.02 (0.015)	0.034 (0.014)**	0.017 (0.015)
θ	0.154 (0.018)***	0.154 (0.018)***	0.151 (0.019)***	0.157 (0.018)**	0.160 (0.018)***
α_0	0.013 (0.004)***	0.013 (0.004)***	0.006 (0.012)***	0.558 (0.221)**	0.738 (0.222)***
α_1	0.134 (0.021)***	0.129 (0.021)***	0.130 (0.020)***	0.153 (0.111)	0.172 (0.098)*
β_1	0.871 (0.020)***	0.871 (0.020)***	0.889 (0.018)***	0.470 (0.126)***	0.465 (0.111)***
γ			0.233 (0.049)***		0.2695 (0.053)***
δ			1.168 (0.166)***		1.690 (0.100)***
df	5.402 (0.468)***	5.540 (0.434)***	5.615 (0.495)***	5.426 (0.434)***	5.921 (0.525)***
d				0.509 (0.039)***	0.457 (0.037)***
LogL	−4,992.73	−4,992.93	−4,970.34	−4,969.82	−4,951.00
AIC	2.8861	2.8856	2.8743	2.8733	2.8637
SIC	2.8967	2.8945	2.8885	2.8853	2.8797
Skewness	−0.060	−0.057	−0.012	−0.013	0.004
Kurtosis	2.547	2.547	2.430	2.458	2.392
Q(10)	26.800	26.644	27.906	23.914	23.237
Q(20)	40.075	39.989	42.157	36.742	36.053
$Q^2(10)$	7.3439	7.0671	9.6792	3.7334	2.9453
$Q^2(20)$	18.348	17.426	18.784	12.573	9.0261
SBT	1.763*	1.768*	0.583	1.812*	0.848
NSBT	0.691	0.813	0.941	0.122	0.256
PSBT	0.898	1.001	2.084	0.439	2.246
JSBT	5.620	6.070	5.260	3.984	5.161
RBD(2)	4.898	3.652	−29.851	2.114	1.642
RBD(5)	3.085	4.774	2.046	3.924	2.322
RBD(10)	7.009	7.363	6.817	5.344	4.398

Notes: Significance at: *10, **5 and ***1 percent levels, respectively; models 1-5 represent GARCH (1, 1), IGARCH (1, 1), APARCH (1, 1), FIGARCH (1, d, 1) and FIAPARCH (1, d, 1), respectively; *df* is estimated degree of freedom for student distribution; *d* is the long-memory parameter; *LogL* is the value of the maximized likelihood; QMLE standard errors are presented in parentheses below corresponding parameter estimates; the AIC and SIC are the Akaike and Schwarz information criteria; the sample skewness and kurtosis are based on the standardized residuals; the Q(10), Q(20), Q(10) and Q2(20) refer to the Ljung-Box statistics with 10 and 20 degrees of freedom based on the standardized and the squared standardized residuals, respectively; SBT, BSBT, PSBT and JSBT are Engle and Ng (1993) diagnostic tests for asymmetry in volatility, they are sign bias test (SBT), negative SBT (NSBT), positive SBT (PSBT) and joint test for sign and size bias (JTSB), respectively; RBD is the residual-based diagnostic for conditional heteroscedasticity of Tse (2002)

(1993) SBT indicates that there is some leverage effect in the results. Consequently, we estimate the APARCH (1, 1) model of Ding *et al.* (1993). The estimation results are shown in the model 3 of Table III. It shows that all the estimated coefficients are very significant. In particular, the estimated δ is significantly different from 2 with GARCH model. The significant coefficient asymmetric term indicates that the leverage effect does exist in the Malaysian equity market. Let $L1$ be the log-likelihood value under the null hypothesis the true model is the GARCH (1, 1) and let $L2$ be the log-likelihood value under the alternative that the true model is APARCH (1,1). The $2(LogL_1 - LogL_0)$ have a $\chi^2(2)$ distribution when the null is true. In our case, the calculated likelihood ratio (LR) is 45.18, in which we are able to reject the null hypothesis at 1 percent level of significance, indicating that the data are generated by a GARCH process in favor of the more flexible APARCH model. This implies that a more flexible model should be used.

Very interestingly, the result shows that sum of coefficients of α_1 and β_1 is more than unity; this leads us to further investigate the persistence of volatility with the FIGARCH models. Thus, we proceed with the estimation of a FIGARCH (1, 1) model, and the estimation result is presented under the model 4 of Table III. It is shown that the parameter describing the conditional mean is positive and that the parameter describing the long memory in volatility, d is also extremely significant with a value estimated equals to 0.509. This shows that neither the GARCH nor IGARCH models are the correct specifications for the conditional variance. Thus, any attempt to using either estimation would produce specification error. Baillie *et al.* (1996) report the effects of estimating stable GARCH processes where the true data generating process is FIGARCH. The sum of the estimated GARCH (1, 1) parameters is always close to one (as above) which implies IGARCH behaviour and suggests that the apparent widespread IGARCH property so often found in high-frequency studies of financial data may well be spurious. The IGARCH process is indeed poor at distinguishing between integrated versus long-memory formulations of conditional variance.

The FIGARCH model, however, is unable to capture the leverage effect shown by the SBT. We re-estimate a FIAPARCH (1, 1) model to account for the leverage effect. The result is shown in the model 5 of Table III. The LR test statistics for FIAPARCH (1, 1) and FIGARCH (1, 1) are 37.64 allows us to reject null hypothesis that the true model is FIGARCH (1, 1) in favor of FIAPARCH (1, 1) model. As we can see, all the coefficients except the α term are statistically significant. The fractional parameter d and asymmetric parameter (δ) are positive and significant. This highlights the fact that, not only are there are long-memory effects but there are also asymmetry effects that should be taken into account. In addition, based on the LR test, we find that the fractionally integrated models provide statistically significant improvement over the non-integrated models. The LR statistics for FIGARCH (1, 1) versus GARCH (1, 1) is 45.82 and for APARCH (1, 1) versus FIAPARCH (1, 1) are 38.68. Additionally, it can be seen from Table III that the FIAPARCH specification outperforms other specification in terms of dialogistic statistics. For instance, both AIC and SIC information criteria select the more flexible model and are in favor of the FIAPARCH model. The standardized residuals from the more flexible model exhibit less skewness and kurtosis than those of restricted models. Both the FIGARCH and FIAPARCH specifications do a better job in terms of taking care of persistence in the conditional volatility, while the FIAPARCH model outperform the FIGARCH model based on the LR test. Generally, the APARCH and FIAPARCH models are better in taking care of the asymmetric effect as shown by the Engle and Ng (1993) diagnostic tests. The Ljung-Box test statistics also indicate that the FIAPARCH specification does a better job than other specifications.

5. Conclusion

This paper investigates the existence of asymmetric effect as well as long-memory properties in the ECM based on Malaysia stock market data. Based on parametric and non-parametric approaches, there are evidences pointing towards the existence of long memory in the volatility of the stock returns. Our study shows that the traditional ARCH/GARCH is insufficient in modeling the volatility persistence in the emerging stock market such as Malaysia. The use of IGARCH model is also too restrictive. When the FIGARCH model is used, the results show that the fractional parameter is significantly different from 0 and 1. This is consistent with the case of developed countries' stock markets. Our result also shows that the FIGARCH is still insufficient to consider the existence of asymmetric effect. Instead, the FIAPARCH specification gives a better result. Essentially, the volatility of the Malaysian stock market not only has long-memory properties but also shows asymmetry effect.

The evidence of long-memory component presented in this study may indicate that financial security prices are not immune to persistent informational asymmetry, especially over a long-time span. Following Anderson and Bollerslev (1997), if we interpret the volatility as a combination of heterogeneous information arrivals, then it may be argued that despite the short-memory information arrivals, the conditional variance of stock return exhibit long-memory characteristics.

Notes

1. Empirical evidence has frequently demonstrated that GARCH (1, 1) process is able to represent a majority of financial time series. A dataset which requires a higher model of GARCH is very rare.
2. Bollerslev and Wooldridge (1992) and Lee and Hansen (1994) have shown the consistency and asymptotic normality of the QMLE for GARCH (1, 1) model, while Baillie *et al.* (1996, 2001) have shown by simulation the consistency and asymptotic normality of the QMLE for FIGARCH model. It is also worth noting that asymptotic properties of QMLE for APARCH and FIAPARCH process have not been formally established yet.
3. Since all of the components of the index do not trade at the same time, there is a lack of synchronization that will generate serial correlation (Lo and Mackinlay, 1990). Thus, it has been argued that an alternative model would parameterize the conditional mean function as an MA(1) rather than an AR(1). Our estimation also shows that both AR(1) and MA(1) perform similarly in terms of removing the serial correlation. As such, we consider the AR(1) model as the most appropriate model for the mean.

References

Anderson, T.G. and Bollerslev, T. (1997), "Heterogenous information arrivals and return volatility dynamics: uncovering the long-run in high frequency returns", *Journal of Finance*, Vol. 3, pp. 975-1005.

Aydogan, K. and Booth, G.C. (1988), "Are there long cycles in common stock returns?", *Southern Economic Journal*, Vol. 55, pp. 141-9.

Baillie, R.T., Bollerslev, T. and Mikkelsen, H. (1996), "Fractionally integrated generalized autoregressive conditional heteroscedasticity", *Journal of Econometrics*, Vol. 74, pp. 3-30.

Baillie, R.T., Han, Y.W. and Kwon, T.G. (2001), "Further long memory properties of inflationary shocks", *Southern Economic Journal*, Vol. 68, pp. 496-510.

Barkoulas, J.T., Baum, C.F. and Tkavlos, N. (2000), "Long memory in the Greek stock market", *Applied Financial Economics*, Vol. 10, pp. 177-84.

Bollerslev, T. (1986), "Generalized autoregressive conditional heteroskedasticity", *Journal of Econometrics*, Vol. 31, pp. 307-27.

Bollerslev, T. and Mikkelsen, H.O.A. (1996), "Modeling and pricing long memory in stock market volatility", *Journal of Econometrics*, Vol. 73, pp. 151-84.

Bollerslev, T. and Wooldridge, J.M. (1992), "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances", *Econometric Reviews*, Vol. 11, pp. 143-72.

Cheung, Y. and Lai, K. (1995), "A search for long memory in international stock market returns", *Journal of International Money and Finance*, Vol. 14, pp. 597-615.

Crato, N. (1994), "Some international evidence regarding the stochastic behavior of stock returns", *Applied Financial Economics*, Vol. 4, pp. 33-9.

Ding, Z., Granger, C.W.J. and Engle, R.F. (1993), "A long memory property of stock returns and a new model", *Journal of Empirical Finance*, Vol. 1, pp. 83-106.

Engle, R.F. (1982), "Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation", *Econometrica*, Vol. 50, pp. 987-1007.

Engle, R.F. and Bollerslev, T. (1986), "Modeling the persistence of conditional variances", *Econometric Reviews*, Vol. 5, pp. 1-50.

Engle, R.F. and Ng, V.K. (1993), "Time-varying volatility and the dynamic behavior of the term structure", *Journal of Money, Credit and Banking*, Vol. 25 No. 3, pp. 336-49.

Greene, M.T. and Fielitz, B.D. (1977), "Long-term dependence in common stock returns", *Journal of Financial Economics*, Vol. 4, pp. 339-49.

Geweke, J. and Porter-Hudak, S. (1983), "The estimation and application of long memory time series models", *Journal of Time Series Analysis*, Vol. 4, pp. 221-38.

Harvey, C.R. (1995), "Predictable risk and returns in emerging markets", *The Review of Financial Studies*, Vol. 8, pp. 773-816.

Hurst, H. (1951), "Long term storage capacity of reservoirs", *Transactions of the American Society of Civil Engineers*, Vol. 116, pp. 770-99.

Kilic, R. (2004), "On the long memory properties of emerging capital markets: evidence from Istanbul stock exchange", *Applied Financial Economics*, Vol. 14, pp. 915-22.

Laurent, S. and Peters, J.P. (2002), "GARCH 2.2: an Ox package for estimating and forecasting various ARCH models", *Journal of Economic Surveys*, Vol. 16, pp. 447-85.

Lee, S.W. and Hansen, B.E. (1994), "Asymptotic properties of the maximum likelihood estimator and test of the stability of parameters of the GARCH and IGARCH models", *Econometric Theory*, Vol. 10, pp. 29-52.

Lo, A.W. (1991), "Long-term memory in stock market prices", *Econometrica*, Vol. 59, pp. 1279-313.

Lo, A.W. and MacKinlay, A.C. (1990), When are contrarian profits due to stock market overreaction? *Review of Financial Studies*, Vol. 3, pp. 175-205.

Lobato, I.N. and Savin, N.E. (1998), "Real and spurious long-memory properties of stock market data (with discussion)", *Journal of Business & Economic Statistics*, Vol. 16, pp. 261-83.

Mandelbrot, B.B. (1971), "When can price be arbitraged efficiently? A limit to the validity of the random walk and martingale models", *Review of Economics and Statistics*, Vol. 53, pp. 225-36.

Nelson, D.B. (1991), "Conditional heteroskedasticity in asset returns: a new approach", *Econometrica*, Vol. 59, pp. 349-70.

Sowell, F. (1992), "Maximum likelihood estimation of stationary univariate fractionally integrated time series models", *Journal of Econometrics*, Vol. 165, p. 188.

Taylor, S. (1986), *Modeling Financial Time Series*, Wiley, New York, NY.

Tse, Y. (2002), "Residual-based diagnostics for conditional heteroskedasticity models", *Econo-metrics Journal*, Vol. 5, pp. 358-73.

Tse, Y.K. (1998), "The conditional heteroscedasticity of the yen-dollar exchange rate", *Journal of Applied Econometrics*, Vol. 193, pp. 49-55.

Yajima, Y. (1985), "On estimation of long memory time series models", *Australian Journal of Statistics*, Vol. 27, pp. 303-20.

Further reading

Black, F. (1976), "Studies of stock market volatility changes", *Proceedings of the American Statistical Association, Business and Economic Statistics Section*, American Statistical Association, Washington, DC, pp. 177-81.

About the authors

Turkhan Ali Abdul Manap is an Assistant Professor in the Department of Economics, Kulliyyah of Economics and Management Sciences of the International Islamic University Malaysia, based in Kuala Lumpur, Malaysia.

Salina H. Kassim is an Associate Professor in the Department of Economics, Kulliyyah of Economics and Management Sciences of the International Islamic University Malaysia, based in Kuala Lumpur, Malaysia. Salina H. Kassim is the corresponding author and can be contacted at: ksalina@iium.edu.my