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Long Memory Features in Return and Volatility of the Malaysian Stock Market

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Abstract

This study aims to investigate the existence of long memory in the Malaysian stock market utilizing daily stock price index from the period 1998:09 to 2009:12. Various ARFIMA-G(ARCH)-type models have been taken into consideration to address this issue, which has led to several interesting conclusions. Firstly, the long memory property exists in both the return and volatility, with and without incorporating the crisis impact. Secondly, the stock volatility is found to be experiencing significant leverage effect especially with the inclusion of the impact of crisis. This implies that the volatility has the tendency to respond to bad news more than good news as compared to the other periods under study. Thirdly, among the various G(ARCH)-type models with different innovation distributions, the Student-t distribution provides better specifications in terms of the long memory volatility processes. In summary, ARFIMA-FIAPARCH model is found to be the most appropriate method of presenting the stylized facts of stock return and volatility in Malaysia.

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1. Introduction

The existence of long memory property in stock return series has become a critical issue for the investment community and academia due to the increasing roles of the stock markets in terms of portfolio diversification. With the presence of long memory, it is believed that the arrival of new market information cannot be fully arbitraged away (Mandelbrot, 1971). Following this, if the information is fully utilized, stock market participants may outperform the market and make consistent speculative profits.

Although the importance of long memory property is well-established in previous literature, many researchers and practitioners argued that the long memory features are less prominent if the market is efficient. Most of the previous studies found that emerging stock market countries are far from efficient due to the increase in the number of retail and institutional investors trading on stock markets. The different reactions in terms of their degree of information, interests and risk profiles, and reactions to news across different times are believed to be producing long memory in the stock return volatility.

It is well-documented that worldwide stock markets react, in terms of returns and volatility, to shocks such as the crash of 1987, the Asian crises in 1997, terrorist attack, and the recent financial crisis of 2007. However, according to Roll (1988), the timing and magnitude of changes in stock returns and volatility differ across markets around the world. Given that globalization has integrated financial markets, the spread of the sub-prime mortgage crisis of 2007, which resulted in the Lehman Brothers and some major financial institutions declaring bankruptcy and many to ask for government bailout to survive, had therefore raised the interest of many stock market participants and researchers to re-examine its impact on the worldwide stock markets.

This study attempts to test if stock returns and volatility exhibit long memory in Malaysian stock price indices from period 1998:09 to 2009:12. This study represents an advance over previous empirical literature in a number of important aspects.

Firstly, while many studies have tested the long memory in stock returns (Sadique and Silvapulle, 2001) or volatility (Law *et al.*, 2007; Cheong *et al*, 2007 and Cheong, 2008), there are none that examine both the returns and volatility simultaneously. Kang and Yoon (2007) advocated that the long memory in return and volatility should be addressed simultaneously given that the long term dependence phenomena are often observed in both the return and volatility. This study, therefore, follows the recent literature to address the dual long memory property in Malaysian stock market.

Secondly, there is a widespread view that investors tend to react asymmetrically when dealing with good and bad news and investors' sentiments are more pronounced when there is a persistence decrease (bear period) as compared to when there is a persistence increase (bull period) in stock prices. Recently, by analyzing the S&P 500 over a sample period of 1928 to 2006, Cunado *et al.* (2008, 2010) found that the stock returns present long memory behavior during both the bull and bear periods, whereas the long range dependence volatility are more prevalent during bear period. In order to determine if investors behave asymmetrically across various periods, this study utilizes the Bry and Boschan (BB, 1971) algorithm to identify the existence of bear and bull periods. Various Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are then adopted to address not only the nature of long memory component, but also the possibility of the leverage effect following the burst of the global crisis. The test results are expected to be similar to the overall period if the effect of the crisis is not dramatic.

Thirdly, most of the recent studies on GARCH-type models highlighted the importance of selecting appropriate innovation distributions. For instance, by considering various GARCH-type models, Tang and Shieh (2006) and Kang *et al.* (2010) suggested that the Student-t and skewed Student-t distributions are more appropriate to take into account the major stylized facts of stock returns. This study, thus, considers the distributional properties of stock returns using the normal, Student-t and skewed Student-t distributions.

The rest of the study unfolds as follows. The next section briefly introduces the method used in testing long memory. Section 3 describes the characteristics of the sample data and presents the findings of this study. Section 4 discusses the most relevant conclusions.

2. Methodology

2.1 Autoregressive Fractional Integrated Moving Average (ARFIMA) model

According to Granger and Joyeux (1980), and Hosking (1981), for the series x_t, t = 1, …, T, the ARFIMA(r, d, s) model can be expressed as

$$\Psi(L)(1-L)^d(x_t-\mu)=\Theta(L)\varepsilon_t \tag{1}$$

$$\varepsilon_t = z_t\sigma_t, \qquad z_t \sim (0,1), \tag{2}$$

where μ is conditional mean and ε_t is independent and identically distributed (i.i.d.) with a variance σ^2, and L is the lag operator as denoted earlier. $\Psi(L)=\psi_1 L+\psi_2 L^2+...+\psi_r L^r$ and $\Theta(L)=\theta_1 L+\theta_2 L^2+...+\theta_s L^s$ are the autoregressive (AR) and moving-average (MA) polynomials lie outside of unit cycles, respectively.

The process is said to be long memory at the long run as long as d > 0 in equation (1). In particular, for $d \in (0, 0.5)$, and $d \neq 0$, the series is covariance stationary and mean-reverting, with shocks disappearing in the long run; for $d \in (0.5, 1)$, the series imply mean-reversion, however, it is not a covariance stationary process as there is no long run impact of an innovation on future values of the process. For $d \geq 1$, the series is nonstationarity and non-mean-reversion. On the contrary, the process is said to exhibit intermediate memory, for $d \in (-0.5, 0)$.

2.2 Fractional Integrated GARCH (FIGARCH) model

Similar research on the volatility has led to an extension of the ARFIMA representation in ε_t^2, leading to the FIGARCH model. Baillie *et al.* (1996) have extended the traditional GARCH model to capture the long memory component in the return's volatility. The FIGARCH(p, ξ, q) model is given by

$$\phi(L)(1-L)^{\xi}\varepsilon_t^2 = \omega + [1-\beta(L)](\varepsilon_t^2 - \sigma_t^2) \tag{3}$$

or

$$\sigma_t^2 = \omega + \beta(L)\sigma_t^2 + [1-\beta(L)]\varepsilon_t^2 - \phi(L)(1-L)^{\xi}\varepsilon_t^2 \tag{4}$$

where $\phi(L) = \phi_1 L + \phi_2 L^2 + ... + \phi_q L^q$, $\beta(L) = \beta_1 L + \beta_2 L^2 + ... + \beta_p L^p$. All the roots of $\phi(L)$ and $[1 - \beta(L)]$ are assumed to stand in outside the unit root.

The FIGARCH model provides greater flexibility for modeling the volatility as it nests GARCH. If $\xi = 0$, the FIGARCH (p, ξ, q) process reduces to a GARCH (p, q) process. The impact of a shock is said to decrease at a hyperbolic rate when $0<\xi<1$. By allowing ξ to take a value within 0 and 1, FIGARCH permits for an intermediate range of persistence.

2.3. The Fractional Integrated Asymmetric Power ARCH (FIAPARCH) model

To take into account both the long memory and asymmetry features in the process of conditional variance behavior, Tse (1998) has extended the FIGARCH(p, ξ, q) by introducing the function $(|\varepsilon_t| - \gamma\varepsilon_t)^{\delta}$ of the APARCH process. Formally, the FIAPARCH(p, ξ,q) can be written as follows:

$$\sigma_t^{\delta} = \omega[1-\beta(L)]^{-1} + \{1-[1-\beta(L)]^{-1}\rho(L)(1-L)^{\xi}\}(|\varepsilon_t| - \gamma\varepsilon_t)^{\delta} \tag{5}$$

where δ, γ and ξ are the model parameters.

Some stylized facts on stock volatility can be captured utilizing the FIAPARCH process. For instance, if $0<\xi<1$, as stated earlier, the volatility exhibits the long memory process. The γ ($-1<\gamma<1$) accounts for the volatility asymmetry, in which positive and negative returns of the same magnitude do not generate an equal degree of volatility. The negative shocks are said to have more impact on volatility than positive shocks when $\gamma>0$, vice versa. The δ ($\delta>0$), is a coefficient for the power term and should be specified by the data. The FIAPARCH process nests the FIGARCH process when $\gamma=0$ and $\delta=2$.

2.4 Various Innovations' Distributions

The parameters of the various-type of GARCH models can be estimated by using non-linear optimization procedures to maximize the logarithm of the Gaussian likelihood function. The log-likelihood of Gaussian or normal distribution (L_{Norm}) can be expressed as

$$L_{Norm} = -\frac{1}{2} T \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \left[\log(\sigma_t^2) + \frac{\varepsilon_t^2}{\sigma_t^2} \right] \quad (6)$$

where T is the number of observations.

However, as highlighted by Tang and Shieh (2006) and Kang *et al.* (2010), the residuals estimated from the GARCH type model often suffer from asymmetry and leptokurtosis. To overcome the leptokurtosis problem, the Student-t distribution can be considered (Cheong, 2008; Kang and Yoon, 2008). Thus, given the random variable $z_t \sim ST(0,1,\nu)$, the log-likelihood function of the Student-t distribution (L_{Stud}) is defined as follows:

$$L_{Stud} = T\left\{ \ln\Gamma\left(\frac{\nu+1}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\ln[\pi(\nu-2)] \right\} - \frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+\nu)\left[\ln\left(1 + \frac{z_t^2}{\sigma_t^2(\nu-2)}\right)\right]\right] \quad (7)$$

where $2 < \nu \leq \infty$, and $\Gamma(\cdot)$ is the gamma function. The parameter ν, representing the number of degrees of freedom, measures the degree of leptokurtosis of the density of residuals. The lower values of ν are the fatter tails of the density. As $\nu \rightarrow \infty$, the Student-t distribution approaches the normal one.

On the other hand, to capture the asymmetry and leptokurtosis, Lambert and Laurent (2001) proposed the skewed Student-t distribution in which by given the random variable $z_t \sim SkST(0,1,k,\nu)$, the log-likelihood function of the skewed Student-t distribution (L_{SkSL}) is defined as follows:

$$L_{SkSt} = T\left\{ \ln\Gamma\left(\frac{\nu+1}{2}\right) - \ln\Gamma\left(\frac{\nu}{2}\right) - \frac{1}{2}\ln[\pi(\nu-2)] + \ln\left(\frac{2}{k+1/k}\right) + \ln(s) \right\}$$
$$-\frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+\nu)\left[\ln\left(1 + \frac{(sz_t+m)^2}{\nu-2} k^{-2I_t}\right)\right]\right] \quad (8)$$

where $I_t = 1$ if $z_t \geq -m/s$ or $I_t = -1$ if $z_t < -m/s$, k is an asymmetry parameter. The constant $m = m(k,\nu)$ and $s = \sqrt{s^2(k,\nu)}$ are the mean and standard deviation of the skewed Student-t distribution. The value of ln(k) can represent the degree of asymmetry of residual distribution. If $\ln(k) > 0$ ($\ln(k) < 0$), the density is right (left) skewed. When $k = 1$, the skewed Student-t distribution equals the general Student-t distribution.

3. Empirical Results

The data set used in this study comprises daily observations of FTSE Bursa Malaysia Kuala Lumpur Composite Index (FBMKLCI) over the period 1998:09 to 2009:12. The daily stock returns are defined as the logarithmic difference of the daily closing index values. The data is extracted from DataStream® database.

Utilizing the BB algorithm, a bear period trend from 2008:01 to 2008:10 has been observed in the Malaysian stock market. Following this, two sub-periods have been identified. Sub-period I covers the observations from 1998:09 to 2007:12 in which the crisis impact has been isolated. Sub-period II (1998:09 to 2008:10) includes the greatest crisis impact and the overall period covers the period from 1998:09 to 2009:12 that includes the observations after the rebound of stock market from the recent bear period.

Table 1 of Panel A provides a summary of statistics of the stock return series. The significant Ljung–Box statistics for the returns, Q(20) and squared returns, Qs(20), indicating the rejection of the null of white noise, asserting that these return series are autocorrelated. The significant Jarque–Bera test statistics indicated that the residuals appear to be leptokurtic. In summary, it is clear that Malaysian stock market exhibits frequent volatilities with extensive amplitude, implying the assumption of normal distribution may not be suitable for capturing asymmetry and tail-fatness in a return distribution.

Table 1. Summary Statistics, ADF Unit Root Tests and KPSS Stationary Tests of Stock Return Series

	A: Sub-Period I	B: Sub-Period II	C: Overall Period
Panel A			
Mean (%)	6.65	4.05	5.07
Std deviation (%)	1.33	1.34	1.29
Skewness	-0.27	-0.40	-0.39
Excess kurtosis	82.16	74.92	77.21
J-B	600267.40^{**}	539718.60^{**}	655709.30^{**}
Q(20)	65.48^{**}	63.96^{**}	63.26^{**}
$Q_S(20)$	1306.65^{**}	1377.61^{**}	1570.71^{**}
Panel B			
ADF	-13.61^{**}	-13.92^{**}	-15.00^{**}
KPSS	0.26	0.44	0.26

Notes: Critical values at 5 percent level are −2.87 for ADF_{μ} and 0.46 for KPSS, respectively. ** indicates significant at 5 percent level.

To check if the return series is I(0), the Augmented Dickey-Fuller (ADF, 1979) unit root test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS, 1992) stationary test are performed (Panel B of Table 1). It is noted that the ADF test results reject the unit root null hypothesis for the stock return series while the KPSS test statistics are insignificant to reject the null hypothesis of stationarity. Taking together, these results suggest that the return series are stationary processes I(0) and hence are relevant for the long memory tests.

3.1 ARFIMA models

This section estimates some specifications of ARFIMA models in detecting the long memory property in the level of return series. Table 2 highlights the ARFIMA parameterization selected using the Akaike Information Criteria (AIC)[1]. An ARFIMA (2,d,2) model is found to best represent the long memory process in stock return series. The estimates of d are statistically significant at the 5 percent level. Thus, the results support that the returns are forecastable and supportive of long memory processes.

Table 2. Estimation Results of the ARFIMA Models

	A: Sub-Period I	**B: Sub-Period II**	**C: Overall Period**
	ARFIMA(2,d,2)	**ARFIMA(2,d,2)**	**ARFIMA(2,d,2)**
μ	0.076	0.044	0.059
	(0.048)	(0.048)	(0.043)
ψ_1	-1.235**	-1.185**	-1.204**
	(0.103)	(0.110)	(0.115)
ψ_2	-0.468**	-0.434**	-0.447**
	(0.090)	(0.097)	(0.097)
d	0.092**	0.096**	0.089**
	(0.027)	(0.026)	(0.024)
θ_1	1.118**	1.072**	1.107**
	(0.122)	(0.128)	(0.132)
θ_2	0.275**	0.249**	0.285**
	(0.076)	(0.044)	(0.059)
ln(L)	-3898.23	-4265.92	-4758.18
AIC	3.397	3.413	3.336
Skewness	-0.010	-0.241	-0.338
Excess Kurtosis	73.015	67.277	70.914
J-B	19300.000**	19503.000**	23386.000**
	[0.000]	[0.000]	[0.000]
ARCH(5)	30.298**	21.722**	25.830**
	[0.000]	[0.000]	[0.000]
Q(20)	38.899**	35.157**	35.373**
	[0.001]	[0.002]	[0.002]

Notes: Standard errors and p-values are in parentheses and brackets respectively. ** and * indicate significant at 5 and 10 percent significance level respectively. ln(L) value is the maximized value of the log likelihood function, and AIC is the Akaike (1974) Information criteria. J-B refers to Jarque-Bera normality test. The ARCH(5) denotes the ARCH test statistic with lag 5 while the Q(20) is the Ljung-Box test statistic for standardized residuals.

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[1] The authors would like to thank the referee for the suggestion of estimating the ARFIMA (r,d,s) by extending the r and s to 3 instead of 2 to ensure that the minimum AIC is selected. The AIC values for various r and s are reported in Appendix A.

Nevertheless, the residuals are mostly negatively skewed, implying that the distribution is non symmetric. The J–B test statistics also reveal that the residuals appear to be leptokurtic. Moreover, the ARCH statistics are highly significant, indicating the existence of ARCH effects in the standardized residuals. The significant Q-statistics denote that the residuals are not independent. These statistics signify the limitations of building the ARFIMA model in the return series and signal the importance of testing the existence of long memory in volatility.

3.2. Estimating ARFIMA-GARCH-type Models[2]

Table 3 and Table 4 provide the estimation results of the ARFIMA-FIGARCH and ARFIMA-FIAPARCH models assuming normal and Student-t innovations' distributions[3].

3.2.1. ARFIMA-FIGARCH

As shown in Table 3, the parameter d remains significant revealing the presence of long memory in return series. For the volatility component, the long memory parameters, (ξs), ranging from 0.445 to 0.484, are all significant at 5 percent significance level, indicating the long-range memory phenomenon for volatilities. The existence of long memory in both return and volatility contradicts the efficient market hypothesis of Fama (1970) that the future return and volatility values are unpredictable.

Besides, the estimates of fat-tailed parameter ν, ranging from 5.435 to 5.529, are statistically significant at the 5 percent level suggesting the usefulness of Student-t distribution in modeling the leptokurtosis of estimated residuals. With reference to the log-likelihood and the AIC as well as Pearson goodness-of-fit test statistics, P(60), the ARFIMA-FIGARCH models with Student-t distributed innovations performs better than those with normal distributions.

[2] The results of ARFIMA(2,d,2)-GARCH(1,1) are not reported but available upon request. In general, the results show that the sum of the estimates of α_1 and β_1 is close to one, indicating that the volatility process is highly persistent.

[3] This study shows the results based on the normal and Student-t distributions only. The estimation results based on skewed Student-t distribution are not reported given that the ln(k) is not statistically significant for all models considered.

Table 3. Estimation Results of ARFIMA-FIGARCH Models

	A: Sub-Period I		B: Sub-Period II		C: Overall Period	
	Normal	**Student-t**	**Normal**	**Student-t**	**Normal**	**Student-t**
μ	0.051*	0.039	0.043	0.028	0.056**	0.041*
	(0.029)	(0.026)	(0.030)	(0.026)	(0.027)	(0.024)
ψ_1	-0.865**	-0.867**	-0.864**	-0.866**	-0.863**	-0.866**
	(0.024)	(0.034)	(0.027)	(0.035)	(0.029)	(0.039)
ψ_2	-0.403**	-0.388**	-0.399**	-0.387**	-0.399**	-0.388**
	(0.027)	(0.044)	(0.029)	(0.042)	(0.029)	(0.044)
d	0.088**	0.077**	0.090**	0.081**	0.086**	0.077**
	(0.026)	(0.024)	(0.027)	(0.023)	(0.025)	(0.021)
θ_1	0.942**	0.928**	0.939**	0.918**	0.943**	0.922**
	(0.033)	(0.039)	(0.035)	(0.040)	(0.035)	(0.043)
θ_2	0.438**	0.410**	0.423**	0.402**	0.433**	0.411**
	(0.034)	(0.048)	(0.037)	(0.047)	(0.035)	(0.048)
ω	1.765	2.869	2.778	2.803	2.210	2.210
	(1.299)	(3.481)	(2.212)	(2.510)	(1.624)	(1.704)
α	0.067	0.154	-0.073	0.063	-0.073	0.014
	(0.184)	(0.223)	(0.128)	(0.187)	(0.124)	(0.161)
β	0.351	0.458	0.268**	0.362	0.261**	0.311
	(0.216)	(0.308)	(0.131)	(0.242)	(0.130)	(0.202)
ξ	0.445**	0.484**	0.476**	0.466**	0.464**	0.448**
	(0.073)	(0.136)	(0.070)	(0.094)	(0.061)	(0.073)
ν		5.529**		5.435**		5.518**
		(0.644)		(0.543)		(0.528)
ln(L)	-2983.20	-2921.77	-3341.83	-3261.01	-3739.89	-3655.50
AIC	2.604	2.551	2.677	2.613	2.625	2.567
Qs(20)	15.257	16.279	8.452	6.960	8.650	6.882
	[0.644]	[0.573]	[0.971]	[0.990]	[0.967]	[0.991]
ARCH(5)	0.493	0.573	0.255	0.114	0.255	0.081
	[0.782]	[0.721]	[0.937]	[0.989]	[0.937]	[0.995]
P(60)	122.218**	60.261	132.885**	56.495	145.331**	60.487
	[0.000]	[0.430]	[0.000]	[0.568]	[0.000]	[0.422]
RBD(5)	2.916	8.791	5.453	2.156	7.290	2.233
	[0.713]	[0.118]	[0.363]	[0.827]	[0.200]	[0.816]

Notes: d and ξ are the long memory parameters for return and volatility process respectively. Standard errors and p-values are in parentheses and brackets respectively. ** and * indicate significant at 5 and 10 percent significance level respectively. ln(L) value is the maximized value of log likelihood function, and AIC is the Akaike (1974) Information criteria. The Qs(20) is the Ljung-Box test statistic for square standardized residuals while the ARCH(5) denotes the ARCH test statistic with lag 5. P(60) is the Pearson goodness-of-fit statistic for 60 cells and RBD(5) represents the RBD statistics with the embedding dimension m = 5.

3.2.2. ARFIMA-FIAPARCH

The estimation results of ARFIMA–FIAPARCH model under the normal and Student-t distributions are reported in Table 4. The values of fractionally differencing parameters (d and ξ) are significantly different from zero, indicating the existence of dual long memory process. However, the results do not find the strong evidence that the long range dependence volatility is more prevalent when the crisis periods are included.

Consistent with the ARFIMA-FIGARCH models, the Student-t distribution provides the best representation than the normal one, given the significant tail parameter (ν), ranging from 5.827 to 6.066 at 5 percent significant level. The insignificant diagnostic statistics, for instance, the Qs(20), ARCH(5), P(60), RBD(5), also further confirm the selection of Student-t distribution to capture time-varying volatility.

Additionally, there is a strong evidence of volatility asymmetry since the (δ) parameters are statistically significant with all the innovation's distributions. In addition, the asymmetric coefficients (γ) are positive and significant in all sub-periods and overall period. In particular, by referring to the Student-t distribution, these γs increased from 0.235 (Sub-Period I) to 0.289 (Sub-period II) and then reduced to 0.250 (Overall Period). Given the significant asymmetric coefficients, the results suggest that bad news have a larger impact of volatility than good news of the similar magnitude, especially when the crisis periods are included, and thus, support the presence of a "leverage effect". It is not surprising as following the burst of the sub-prime crisis of 2007, a series of bad news has caused the U.S. stock price index to plunged from 13930 (2007:10) to as low as 9325 (2008:10) points and most of the worldwide stock markets followed, resulting in a downturn in their stock markets.

In fact, Awartani and Corradi (2005) and Evans and McMillan (2007) also found that GARCH-class of models that do not allow for asymmetries in the volatility process are beaten by asymmetric GARCH models. As seen in the tables, according to the AIC, the ARFIMA-FIAPARCH models fit the return series better than the ARFIMA-FIGARCH models.

Table 4. Estimation Results of ARFIMA-FIAPARCH Models

	A: Sub-Period I		B: Sub-Period II		C: Overall Period	
	Normal	Student-t	Normal	Student-t	Normal	Student-t
μ	0.010	0.015	0.000	0.000	0.020	0.017
	(0.033)	(0.028)	(0.032)	(0.028)	(0.028)	(0.026)
ψ_1	-0.863**	-0.866**	-0.862**	-0.866**	-0.861**	-0.866**
	(0.017)	(0.019)	(0.019)	(0.020)	(0.020)	(0.022)
ψ_2	-0.381**	-0.387**	-0.376**	-0.387**	-0.380**	-0.389**
	(0.032)	(0.029)	(0.038)	(0.030)	(0.034)	(0.032)
d	0.092**	0.081**	0.092**	0.088**	0.086**	0.083**
	(0.026)	(0.028)	(0.024)	(0.023)	(0.023)	(0.021)
θ_1	0.933**	0.925**	0.930**	0.913**	0.934**	0.917**
	(0.029)	(0.028)	(0.028)	(0.028)	(0.027)	(0.029)
θ_2	0.411**	0.406**	0.398**	0.397**	0.410**	0.407**
	(0.040)	(0.038)	(0.041)	(0.037)	(0.038)	(0.037)
ω	5.866**	6.494**	6.540**	6.502**	5.848**	5.570**
	(1.785)	(2.191)	(2.159)	(2.170)	(1.783)	(1.965)
α	0.212*	0.237**	0.065	0.165	0.046	0.100
	(0.128)	(0.110)	(0.114)	(0.109)	(0.107)	(0.122)
β	0.547**	0.578**	0.436**	0.513**	0.415**	0.445**
	(0.147)	(0.120)	(0.114)	(0.124)	(0.111)	(0.144)
ξ	0.485**	0.507**	0.491**	0.497**	0.480**	0.480**
	(0.059)	(0.058)	(0.051)	(0.052)	(0.046)	(0.049)
News, γ	0.286**	0.235**	0.316**	0.289**	0.289**	0.250**
	(0.103)	(0.073)	(0.096)	(0.072)	(0.083)	(0.065)
Power, δ	1.185**	1.296**	1.294**	1.360**	1.320**	1.429**
	(0.194)	(0.181)	(0.186)	(0.156)	(0.193)	(0.183)
ν		6.066**		5.827**		5.938**
		(0.678)		(0.605)		(0.600)
ln(L)	-2964.01	-2911.16	-3320.58	-3247.65	-3719.47	-3644.12
AIC	2.589	2.544	2.662	2.604	2.612	2.560
	2.619	2.576	2.690	2.635	2.637	2.587
	2.589	2.544	2.662	2.604	2.612	2.560
	2.600	2.556	2.672	2.615	2.621	2.570
Qs(20)	19.269	19.830	8.383	8.496	8.760	7.723
	[0.375]	[0.342]	[0.972]	[0.970]	[0.965]	[0.982]
ARCH(5)	1.157	1.181	0.331	0.430	0.318	0.207
	[0.328]	[0.316]	[0.894]	[0.828]	[0.902]	[[0.960]
P(60)	113.658**	63.236	124.307**	60.856	135.419**	56.497
	[0.000]	[0.329]	[0.000]	[0.409]	[0.000]	[0.568]
RBD(5)	7.954	4.695	2.265	-2.003	4.533	0.285
	[0.159]	[0.454]	[0.811]	[1.000]	[0.475]	[0.998]

Note: see Table 3.

4. Conclusions

By using daily stock price index spanning from period 1998:09 to 2009:12, this study has investigated the presence of dual long memory property in the Malaysian stock market following the U.S. sub-prime crisis in year 2007, using various ARFIMA-G(ARCH)-type models. This study also explores the relative importance of the asymmetry and distributional assumption in modeling stock return series. Several salient points have emerged from the current study. Firstly, the long memory property exists in both the return and volatility with and without incorporating the crisis impact.

Secondly, this study found that both ARFIMA-FIGARCH and ARFIMA-FIAPARCH models fit the data well. However, the FIAPARCH was able to separate the impact of good and bad news. Given the significant asymmetric parameter, this study supported the leverage effect. In particular, stock volatility is found to be experiencing significant leverage effect especially with the inclusion of the impact of crisis. This implies that volatility has the tendency to respond to bad news more than good news as compared to the other periods under study.

Thirdly, among the various ARFIMA-G(ARCH)-type models with different innovation distributions, the Student-t distribution provides better specifications in terms of long memory volatility processes. The estimated results with Student-t distribution outperform the normal and skewed Student-t in capturing leptokurtosis in residuals, which indicates that specifying the error distribution is, as important as, modeling the long memory and asymmetric component of return series.

Overall, ARFIMA-FIAPARCH model with Student-t distribution is found to be the most appropriate method of presenting the stylized facts of stock return and volatility in Malaysia.

Appendix

Appendix A. AIC Values for ARFIMA Models with r, s = 0, 1, 2, 3

	s = 0	s = 1	s = 2	s = 3
r = 0				
Sub-Period I	3.4217	3.4183	3.4187	3.4132
Sub-Period II	3.4340	3.4307	3.4304	3.4260
Overall Period	3.3600	3.3577	3.3577	3.3466
r = 1				
Sub-Period I	3.4188	3.4190	3.4034	3.3983
Sub-Period II	3.4313	3.4309	3.4170	3.4143
Overall Period	3.3581	3.3581	3.3397	3.3369
r = 2				
Sub-Period I	3.4176	3.3990	**3.3973**	3.3976
Sub-Period II	3.4290	3.4137	**3.4129**	3.4135
Overall Period	3.3498	3.3370	**3.3358**	3.3362
r = 3				
Sub-Period I	3.4122	3.3977	3.3985	3.3981
Sub-Period II	3.4280	3.4166	3.4173	3.4184
Overall Period	3.3460	3.3361	3.3367	3.3375

Note: Numbers in bold are the selected model with minimum AIC.

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