Testing for Long Memory in the Nigerian Stock Market

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Abstract

This paper examines the issue of long memory dependence in the Nigerian stock market in order to provide fresh evidence on its efficiency. Using monthly returns from the Nigerian Stock Exchange for the period January 2000 to July 2016 and applying the GARCH-class models, the results show a significant evidence of long memory in the data. The findings reject the weak form efficiency hypothesis as past information can be used in forecasting returns in the stock market. It is recommended that further research to identify the causes of the inefficiency should be undertaken. On its part, the SEC should strengthen measures that boost liquidity and encourage investor education as well as other initiatives that could drive the market closer to efficiency.

Key words: long memory, Nigerian Stock Market, weak form efficiency, stock returns.

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1. Introduction

A major issue in financial economics is the behaviour of stock returns over both the long and short horizons. Stock returns are said to demonstrate positive serial correlation over short horizons but negative serial correlation over longer horizons (Cheung, 1995). According to the weak form efficient market hypothesis (EMH), the current share price should fully reflect the information contained in previous price history. This implies that the share price does not exhibit serial correlation, or 'memory' (Bond & Dyson, 2008).

Understanding the nature of the long memory dynamics of a stock market has important implications. First, long memory in stock returns will render invalid any statistical inference concerning asset pricing models (Cheung, 1995). Second, in the presence of long memory, the arrival of new market information will not be automatically reflected in prices. This implies that asset prices will not be fully arbitraged away (Kiliĉ, 2004). Third, the presence of long memory in asset prices invalidates the weak-form efficiency of stock markets because past price information can be useful in predicting future returns. The weak-form EMH requires that asset prices should reflect all previous price information.

A few studies have examined long memory dynamics in the Nigerian stock market (see e.g., Gyamfi et al. (2016); Ngene et al. (2015); Thupayagale (2010); Anoruo and Gil-Alana(2010)). However, empirical findings have been mixed, prompting the need for further investigation. The absence of a clear consensus on this issue coupled with policy implications of market inefficiency has provided the appropriate background for this paper. In order to contribute to this debate this paper examines the issue of long memory dynamics (long term dependence) in the Nigerian stock market using monthly returns data obtained from the Nigerian Stock Exchange (NSE) All Share Index (ASI).

The rest of this paper is organized as follows. Section 2 reviews related literature while section 3 presents the data and is dynamic characteristics. Section 4 presents the empirical results while section 5 provides conclusions and recommendations.

2. Literature review

Long memory issues arise in various different fields, such as hydrology, internet traffic, economics and finance(Ohanissian, Russell, & Tsay, 2007; Yalama & Celik, 2013). In economics and finance, the issue has been investigated in stock markets, exchange rates and bond returns. A large body of literature exists that examines stock prices in the context of long memory processes. However, despite over six decades of research, there has been no consensus in the literature with respect to the presence or absence of long memory.

A variety of long memory tests has been employed in the literature like the classical rescaled range (R/S) analysis suggested by Hurst (1951); the modified R/S analysis proposed by Lo (1991); the spectral regression method developed by Geweke and Porter-Hudak (1983)(the GPH method) and the long memory processes in the context of conditional variance by extending the GARCH models of Bollerslev (1986) and the exponential ARCH models of Nelson (1991) introduced by Baillie et al. (1996) and Bollerslev and Mikkelsen (1996). In addition, Breidt et al. (1998) proposed a long memory stochastic volatility model by incorporating a fractionally integrated process in a standard volatility scheme (Pong, Shackleton, & Taylor, 2008).

The existence of long memory characteristics has mostly been supported in previous studies of stock markets (Al-Shboul and Anwar (2016); Li et al. (2016); Gil-Alana et al. (2015); Huang et al. (2015); Yalama and Celik (2013) and Lin and Fei (2013)). However, there is a body of literature contradicting their findings (Thupayagale (2010); Lux (1996); and McMillan and Thupayagale (2009)).

In the African context, Gyamfi, Kyei, & Gill, (2016) examine the degree of long memory dependence in asset returns and volatility of the Nigerian and Ghanaian Stock index. Employing the Hurst exponent to measure the degree of long-memory, the authors found a strong evidence of the presence of long-memory in both returns and volatility of the indices studied, suggesting that neither of the two markets is weak-form efficient, implying opportunities for abnormal returns.

In a related study using a larger number of countries, Thupayagale (2010) investigate various aspects of long memory behaviour in several African stock markets. His empirical estimates demonstrate that African Stock markets mainly display a predictable component and generally have a long memory component associated with their stock returns, while evidence of long memory in stock return volatility is mixed. Specifically, employing a HYGARCH model, he finds no evidence of long memory in volatility for Botswana, Mauritius, Morocco and Tunisia. While for South Africa, Namibia, Ghana, Kenya, Tunisia and Zimbabwe markets, volatility was characterised by long memory. The results for Nigeria appeared conflicting. One aspect of the results shows explosive volatility persistence, suggesting the absence of long memory in equity return volatility in the market. A second aspect of the result is that Nigeria displayed evidence of long memory in stock returns when the ARFIMA-FIGARCH model was applied. Finally, the results obtained indicated that volatility lacks a predictable component.

In a more recent study using several African countries, Ngene, Tahb, & Darrat (2015) explore the question of whether weekly stock returns and variance in those markets exhibit long memory behaviour. Using a semi-parametric Robinson test and the ARFIMA-FIEGARCH parametric methods and without accounting for structural breaks, the study presented evidence of long memory in mean returns for Morocco, Mauritius and Tunisia. The results also document evidence of long memory in variance in Egypt, Kenya, Mauritius, Morocco, South Africa and Tunisia. These findings contradict market efficiency as they imply the predictability of stock returns and their variances. However, when structural breaks are introduced in the models, the authors find consistent evidence for short memory both in mean and variance across the markets. Furthermore, the evidence suggests significant structural shifts in both returns and variance in the Nigerian market. When structural breaks were ignored, their results indicate the existence of long memory components in stock returns and variance. However, once structural breaks were introduced in the testing models, the long memory evidence significantly dissipated and the results support short memory behaviour instead. These findings suggest that long memory inferences can be affected by episodes of structural breaks which in turn could disguise short memory behaviour. Consequently, they conclude that caution is warranted when interpreting long memory inferences in the presence of structural breaks. In the same vein, Anoruo and Gil-Alana(2010) earlier examined the behaviour of stock prices in several African countries by means of fractionally integrated techniques. The authors could not find evidence of long memory in returns.

3. Data and Methodology

In order to estimate the long memory property of Nigerian stock market, monthly observations of the Nigerian All Share Index from January 2000 to July, 2016 was used. The data was obtained from the website of the Central Bank of Nigeria. To calculate returns, the series was converted into log using the formula $r_t = \log(p_t / p_{t-1}) \times 100$, where r_t is the return, p_t is the current share index and p_{t-1} is the index for the previous period.

Figures 1 and 2 plot the monthly price index and monthly return series respectively. The levels of the series exhibit a pronounced upward trend up to 2008 before a huge drop thereafter. Of recent, we can observe a downward trend reflecting current bearish declines. The returns in figure exhibit volatility clustering as periods of low volatility intermingle with periods of high volatility.

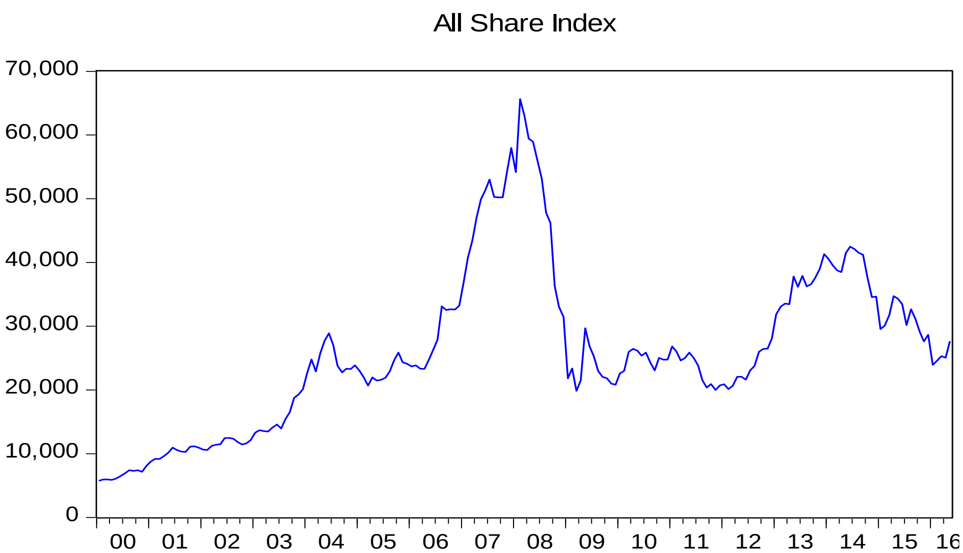

Figure 1: Levels of the monthly price index

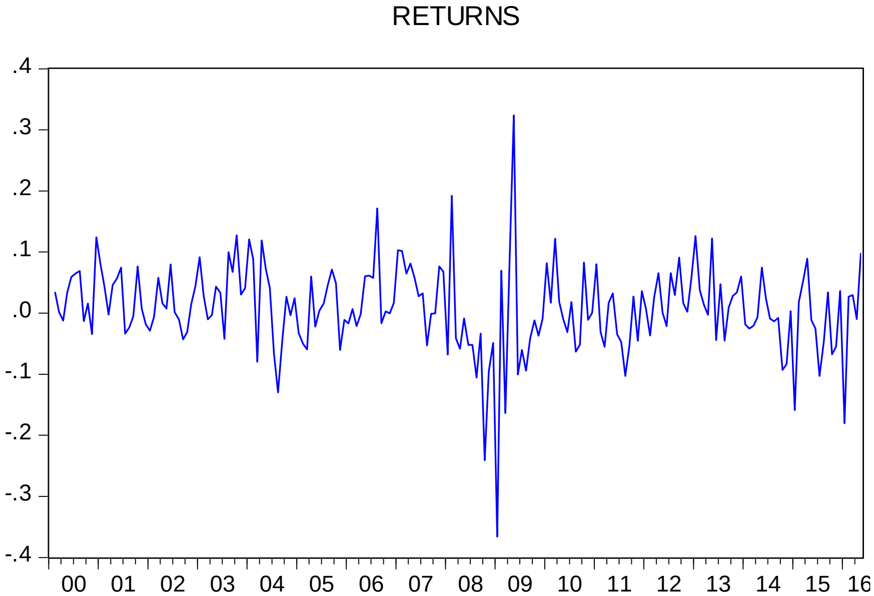

Figure 2: monthly return series

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was used to investigate long memory in returns of the Nigerian stock market. The GARCH model was introduced by Bollerslev (1986) where the current conditional variance depends on its own lagged values and the variance includes both autoregressive and moving average elements. The model can be described as follows:

$$r_t = \mu_t + \varepsilon_t \quad (1)$$

Where $\varepsilon_t / \psi_t \sim iid \quad N(0, \sigma_t)$

$$\sigma^2{}_t = \omega + \beta\sigma^2_{t-1} + \alpha\varepsilon^2_{t-1} \quad (2)$$

where,

r_t	=	dependent variable return
μ_t	=	the conditional mean
σ^2_t	=	the conditional variance
ω	=	the unconditional mean value which is constant
σ^2_{t-1}	=	is the GARCH term which capture information on the past forecast error variance

ε_{t-1}^2 = the ARCH term which capture information on volatility from the past period

The coefficients α and β are expected to be positive to ensure positive conditional variance. The sum of the parameters $\alpha+\beta$ measures the persistence of shock on volatility. The shock to volatility would be unstable if $\alpha+\beta>1$, $\alpha+\beta<1$ is needed in order to make the unconditional variance finite (Bollerslev 1986, Nelson 1991; Abdullahi, Muhammad, & Kouhy, 2014).

Baillie, Bollerslev and Mikkelsen (1996) introduced the fractionally integrated GARCH (FIGARCH) model which captures the long memory in conditional variance and allows the autocorrelation in volatility to die at slow hyperbolic rate. The FIGARCH $(1,d,1)$ can be written as:

$$\sigma_t^{\ 2} = \omega + \left[1-\beta(L)\right]^{-1} + \left\{1-\left[1-\beta(L)^{-1}\right]\phi(L)(1-L)^d\right\}\varepsilon^2{}_t \tag{3}$$

As reported by Davidson (2004), d is the fractional integrated parameter that captures long memory and L the lag operator. The memory parameter increases as *d* approaches zero. To ensure that the conditional variance of the FIGARCH (1,*d*,1) is positive for all *t*, the parameters must take the form $0 \le d \le 1$. The superiority of the FIGARCH model is that it permits three different conditions: the intermediate range of persistence (long memory) when $0<d<1$, infinite persistence when $d=1$ and geometric decay when $d>1$ (Abdullahi, Muhammad, & Kouhy, 2014).

4. Empirical Results

Table 1 reports the parameter estimates for the GARCH (1,1) and FIGARCH models. The second column of the table reports the results for the GARCH (1,1) model. As can be seen from the results, the estimated coefficients for the conditional variance equation α and β are positive and significant for the share index returns. The results further demonstrate that the model observes positive constraint restrictions. In addition, the estimates for the measure of persistence, $\alpha+\beta$, is 0.919, indicating high persistence in the conditional volatility. The finding therefore shows that the stock market exhibits high persistence in its index returns which also implies long memory over the period of study.

The estimated results of the FIGARCH model (presented in third column of the table) indicate that the long memory parameter, *d*, is found to be 1.052 which is positive and significantly different from zero. Moreover, the results show that the coefficient estimate for β is positive and significant with value higher than that of the GARCH (1,1) model. Furthermore, there is evidence that the returns of share index for Nigeria can be predicted using their past values, as the results from the FIGARCH model demonstrate. This suggests that the stock prices do not incorporate all the necessary price information in the market. At the 5% level of significance, the diagnostic tests reveal no evidence of serial correlation or ARCH effects in both the GARCH and FIGARCH models which confirm the fitness of the models (see the Q-Statistics and the ARCH LM tests). Looking at the Box-Pierce Q statistics under the null hypothesis of no autocorrelation and Engle's LM ARCH test under the null hypothesis of no ARCH effects, one concludes that the GARCH (1,1) does a good job in modelling the dynamics of the return series. The higher value of the log likelihood for FIGARCH model supports its superiority over the standard GARCH model.

Table 1: Estimation Results and Diagnostic Tests

	GARCH	FIGARCH
μ	0.016*(3.741)	0.015*(3.414)
ω	0.000(2.647)	0.000 (2.026)
α	0.213*(2.647)	-0.340(-0.783)
β	0.706*(12.86)	0.633*(5.395)
d		1.052(2.489)
$\alpha+\beta$	0.919	0.800
Q(20)	16.44[0.562]	16.67[0.545]
ARCH(10)	0.767[0.661]	0.548 [0.853]
Log(L)	256.7	257.18

Note: Figures in bracket are the *t* statistic beside the parameters. *Q (20)* is the Box-piers test Q-statistics of order 20 for the standardised residuals. *ARCH (10)* is the t-statistics of the homoscedasticity test with 10 lags. P-values are reported in the square bracket. Significant at 1% and 5% level are represented by * and **, respectively. Log (L) represents the logarithm maximum likelihood function.

5. Conclusion and Recommendation

A key finding emanating from this study is the presence of long memory which implies that the market is weak form inefficient. It means that previous prices can be good predictor of future prices. A number of implications follow from the above results. For research there is the need for further investigation into the reasons of the observed inefficiency of the market. There is also the implication that the regulatory authorities, especially the SEC, need to strengthen measures to boost liquidity and encourage investor education as these are required to drive the market closer to efficiency.

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