HOW PERSISTENT ARE NIGERIAN SECTOR STOCKS? A LONG MEMORY ANALYSIS

Abiodun M. Adetokunbo[1], Oluwasegun B. Adekoya[2] and Ismail O. Fasanya[1,2,3]

[1]Department of Economics, Augustine University, Epe, Lagos, Nigeria and
[2]Centre for Econometrics and Allied Research (CEAR), University of Ibadan, Nigeria
[3]Department of Economics, Federal University of Agriculture, Abeokuta, Ogun State, Nigeria

ABSTRACT

This paper studies the long range dependence of ten sectors of Nigerian stock market using data from January, 2007 to December, 2016. Rescaled (R/S) analysis and fractional integration were used to examine the market efficiency of the sector's stocks. The findings indicate a rejection of the hypothesis of random walk in the sectoral prices, thus indicating that the Nigerian sectoral stock prices are largely inefficient. Only the Agriculture stock prices seems to be efficient. Therefore, stock market traders can strategically predict the stock prices of the sectors except Agriculture to earn abnormal returns.

Keywords: Stock price; Market efficiency; Persistence; R/S analysis; Fractional integration

JEL Codes: C22; G12

1. INTRODUCTION

Modelling the long-range dependence in asset returns has been an interesting subject for both academics and policy makers over time. Understanding the existence of long memory in asset prices through efficiency market hypothesis (EMH) in its weak form is crucial for investors, portfolio managers and policy makers. It implies that historical sequence prices or security returns are immediately embodied in asset prices. This guides the decisions of investors and allows potential investors to formulate decisions based on specific information (Fama and French, 1988; Sensoy and

Tabak, 2016; Mensi et al., 2018). For this reason, testing this hypothesis has important implications for optimal asset allocation, investment strategies and forecasting.

In developed markets, persistency in the stock market has been the issue of considerable research by financial experts, the outcome of which is a strong measure of consensus among economists on the validity of the weak and semi-strong forms of the EMH for the major developed countries (Fama, 1970; Ross and Westerfield, 1988). However, the EMH debate has also been carried into the emerging markets sparsely and the conclusions of the studies have been mixed (Gandhi, Saunders and Woodward, 1980; Cooper, 1982; Parkinson, 1987; Ayadi, 1984; Dickinson and Muragu, 1994; Adelegan, 1995; Matome, 1998; Olowe, 1999).

In addition to the scarce literature on Africa, one thing that is also conspicuously scanty in the literature is sector specific analysis. Most of the studies in the literature essentially focus on inter-country financial market spillovers which account for spillovers across countries/international financial markets. Of course, the outcome of such analyses offers useful insights to foreign portfolio investors/managers on how to diversify their asset base in the international financial markets. However, domestic investors within a country would also require information on how to diversify their assets within the domestic sector stocks. Such information can only be teased out from sectoral stocks returns; that is, spillovers among sector-stock assets within the same domestic economy. The only few recent studies dealing with intra-country spillovers are Dean et al. (2010) focusing on Australia; Karmakar (2010) on India; Raimony and El-Nader (2012) on Jordan; Diebold and Yilmaz (2012), Weber (2013), and Cronin (2014) focusing on US; Duncan and Kabundi (2013) on South Africa; Kanga et al. (2013) on Korea; and Wahyudi and Sani (2014) on Indonesia.

On the basis of these limitations in the literature, the contribution of this paper is in two folds. First, our paper focuses on sectoral level analysis drawing evidence from Nigeria. Some of the attractions to Nigeria are highlighted as follows. According to the 2015 KPMG report, in the whole of Africa, Nigeria has one of the largest pools of investment capital with approximately five million registered capital market investors. Furthermore, the report also showed the significance of the Nigerian financial markets in servicing the largest economy in sub-Saharan Africa (KPMG report, 2015), hence, the database is more likely to provide very rich and solid information about the dynamic behaviour of investors as well as the managers of the financial institutions. Second, it contributes methodologically. In addition to the popular R/S analysis developed by Hurst (1951), we introduce the fractional integration. In all, three forms of techniques are employed for the sake of robustness- non-parametric approach (R/S analysis), parametric approach (based on Robinson, 1994) and semi-parametric techniques (based on Robinson, 1995a,b).

We present the remainder of this paper as follows. Second 2 opens the plethora of past studies, Section 3 gives the methodology and data description. In Section 4, we render the presentation and discussion of results including the robustness checks, and Section 5 highlights the policy implications and concludes the paper.

2. LITERATURE REVIEW

Long term dependence of stock markets has been a guide for practitioners and academics in making investment decisions as decisions to curb abnormal profit can be made when there is vivid information on behavioural pattern of stock prices and returns. Literature has detailed record of studies that had considered sectoral pattern of stock markets.

Studies from the Asian emerging market has examined persistence and weak form efficiency of stock markets. Ruan et al. (2018) use the MF-DFA to examine the multifractal property of Shanghai and Hong Kong stock markets. They show that the considered stock markets reveal multifractality. Furthermore, the market efficiency of Shanghai stock market is improved after the implementation of Shanghai-Hong Kong Stock Connect. The evidence of cross-correlation between the two markets is stronger in the long run than in the short run. Evidence of multifractal properties in the CSI 800 index of Chinese stock market was also shown (Zhu and Zhang, 2018). In addition, Cao et al. (2013) investigate the asymmetric multifractal scaling behaviour of Chinese stock markets and show that the multifractality degree of uptrend Chinese stock markets is stronger than that of downtrend Chinese stock markets. They find strong asymmetric correlations in large fluctuations than in small fluctuations.

Tabak and Staub (2016) tested the Random walk hypothesis by examining Brazilian sectoral equity market. The authors employed Variance ratio statistics with derived heteroscedasticity-consistent distributions using a weighted bootstrap method. The result indicated that all sector indices obeys random walk hypothesis with weekly returns except for basic industries. Random walk hypothesis can be used to price assets and build financial models. He and Chen (2010) investigated the causes and multifractality features of Brent and WTI. Using multifractal detrended fluctuation analysis (MF-DFA) and multifractal singular spectrum analysis (MF-SSA) there exist multifractal features in both markets. Shuffling original time series eliminated the market memories but price fluctuations distribution remains the same. In monofractal sense, WTI is more persistent than Brent. In multifractal sense, the width of multifractal spectrum of WTI market is narrower than that of Brent.

Mensi et al (2016) explores the efficient market hypothesis of 10 sector indices of Islamic stock market and examines the effects of the GFC on the level of efficiency using the MF-DFA method. The results provide strong evidence that the level of market efficiency varies over time and decreases after market collapse. The Islamic sectoral market indices are more efficient in the long term than in the short term. Shahzad, et al (2017) examines the power law properties of 11 US credit and stock markets at industry level. Using multifractal detrended fluctuation analysis (MF-DFA) and multifractal detrended cross-correlation analysis (Mf-DXA), the credit default swap (CDS) markets are relatively more inefficient than their equity counterparts. Banks and financial credit markets are relatively more efficient. CDS and equity indices is the most inefficient sector of the US economy.

3. METHODOLOGY

3.1 Data description

This paper covers returns of ten (10) different sectoral stock prices. These sectors include, Agriculture (AGR); Consumer goods (CGD); Conglomerate (CGL); Construction (CON); Financial Services (FIN); Health (HTH); Industrial (IND); Natural Resources (NTR); Oil and Gas (OGS); Service (SVS). The sample period runs from January 2007 to December 2016. The scope and frequency of our study is based on data availability. Data on the monthly sectoral stock prices are obtained from http://www.cashcraft.com/plistorder.php

3.2 Rescaled Range Analysis (R/S Analysis)

This is a non parametric approach to measure the level of efficiency using Hurst exponent. This technique was developed by Hurst (1951) whose original methodology was applied to detect long memory in hydrologic time series and later augmented by Mandelbrot (1972), Peters (1991, 1994) and others for analysis of the financial markets. This Hurst exponent algorithm of R/S analysis for the financial data is well documented in the work of Mynhardt et al. (2014) which is presented below.

1. A time series of length M transforms into one of length N =M –1 using logs and converting prices into returns:

$$N_i = log\left(\frac{Y_{t+1}}{Y_t}\right), \quad t = 1,2,3, \dots\dots, (M-1) \qquad (1)$$

2. This period is divided into contiguous A sub-periods with length n, so that A_n =N. Then, we identified each sub-period as I_a, given the fact that a =1, 2, 3...,A. Each element I_a is represented as N_k with k = 1, 2, 3..., N. For each I_a with length n, the average and e_a is defined as:

$$e_a = \frac{1}{n}\sum_{k=1}^{n} N_{k,a}\,, \qquad \mathrm{k} = 1, 2, 3..., \mathrm{N};\ \ \mathrm{a} = 1, 2, 3..., \mathrm{A} \qquad (2)$$

3. Accumulated deviations $X_{k,a}$, from the average e_a for each sub-period I_a are defined as:

$$X_{k,a} = \sum_{i=1}^{k}(N_{i,a} - e_a) \qquad (3)$$

The range is defined as the maximum index $X_{k,a}$ minus the minimum $X_{k,a}$, within each sub-period (I_a):

$$R_{I_a} = max(X_{k,a}) - min(X_{k,a}), \quad 1 \leq k \leq n \qquad (4)$$

4. The standard deviation S_{Ia} is calculated for each sub-period I_a:

$$S_{I_a} = \left(\frac{1}{n}\sum_{k=1}^{n}\left(N_{i,a} - e_a\right)^2\right)^{0.5} \qquad (5)$$

5. Each range R_{I_a} is normalised by dividing by the corresponding S_{I_a}. Therefore, the re-normalized scale during each sub-period I_a is R_{I_a}/S_{I_a}. In step 2 above, we obtained adjacent sub-periods of length n. Thus, the average R /S for length n is defined as:

$$\left(\frac{R}{S}\right)_n = \frac{1}{A}\sum_{i=1}^{A}\frac{R_{I_a}}{S_{I_a}} \qquad (6)$$

6. The length n is increased to the next higher level, (M-1) / n, and must be an integer number. In this case, we use n –indices that include the initial and ending points of the time series, and Steps 1-6 are repeated until n = (M-1)/2.

7. The least square is used to estimate the equation log (R/S) = log (c) + H*log (n). The angle of the regression line is an estimate of the Hurst exponent (H). The Hurst exponent H changes over the interval [0, 1].

Based on the values of the Hurst exponent, the series can be classified into three categories. The first category is when the Hurst exponent is within the range $0 \leq H < 0.5$, the distribution has a flat tail, hence the series are anti-persistent and returns are negatively correlated (Efficient Market Hypothesis (EMH) not confirmed); in the second category, the EMH is confirmed when $H = 0.5$, there is no memory in the series hence data are random, the data are normally distributed, returns are uncorrelated; and in the last category, the EMH is not confirmed when $0.5 < H \leq 1$. In this case, there is memory in the series, hence the distribution has fat tails, the series are persistent, and returns are positively correlated.

3.3 Fractional Integration Approach

In addition to the non parametric technique, we also employ both parametric and semi-parametric fractional integration or I(d) models. Consideration of these models were motivated by the observation that the estimated spectrum in many aggregated series exhibits a large value at the zero frequency, which is consistent with nonstationary behaviour. However, it becomes close to zero after differencing, which suggests over-differentiation (Granger, 1980; Granger and Joyeux 1980). For this purpose we need to define first an integrated of order 0 (or I(0)) process, which is a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Then, a process is said to be integrated of order d (and denoted by I(d)) if it can be represented as:

$$(1 - L)^d x_t = u_t, \qquad t = 1,2,3, \ldots.., \tag{7}$$

with $x_t = 0, t \leq 0,$ L is the lag operator (i.e., $Lx_t = x_{t-1}$), and where u_t is I(0). Fractional integration takes place when d is a fractional value. In this context, d plays a crucial role since it will be an indicator of the degree of dependence of the time series. Thus, the higher the value of d is, the higher the level of association will be between the observations. In addition, the process admits an infinite Moving Average representation such that, assuming, for instance that u_t is white noise,

$$x_t = \sum_{k=0}^{\infty} \beta_k u_{t-k} \tag{8}$$

with $\beta_k = \frac{\Gamma(k+d)}{\Gamma(k+1)\Gamma(d)}$ where Γ (x) means the Gamma function. Thus, the impulse responses are also affected by the magnitude of d, and the higher the value of d is, the higher the responses will be. In this context, if $d > 0$ in (1), x_t displays the property of long memory, so-named because of the strong degree of association between observations far distant in time. Moreover, if $0 < d < 0.5$, x_t is covariance stationary, and if $0.5 \leq d < 1$, x_t becomes non-stationary, in the sense that the variance of the partial sums increase in magnitude with d; Nevertheless, in both cases (i.e. with $d < 1$), the series will be mean reverting, with shocks having temporary effects, and disappearing in the long run (i.e., $\beta_k \rightarrow 0$ as $k \rightarrow \infty$). On the other hand, if $d \geq 1$, the shock will be permanent, lasting forever unless strong policy measures are adopted.

In the following section we estimate the differencing parameter d by using both parametric and semi parametric approaches. For the former we use a Whittle estimate in the frequency domain as proposed in Dahlhaus (1989) along with a parametric

Lagrange Multiplier (LM) test due to Robinson (1994) that has the advantage that it remains valid even in nonstationary contexts (d ≥ 0.5). The results were practically identical in the two cases. The test of Dahlhaus (1989) considers the following null hypothesis:

$$H_0: d = d_0 \tag{9}$$

for any real value d_o, in the model given by Eq. (7), where xt can be the errors in a regression model of form:

$$y_t = \Phi^{\mathrm{T}} z_t + x_t, \qquad t = 1,2,3, \ldots \ldots, \tag{10}$$

where y_t is the time series we observe and z_t is a (kx1) vector of deterministic terms that might include a constant and a time trend. This test has a standard null limit distribution and its functional form can be found in any of the numerous empirical applications of the tests, (see, Gil-Alana et al., 2012; Abbritti et al., 2016; Gil-Alana et al., 2018, among others). Additionally, we use a semi parametric approach of Robinson (1995) that is also based on the Whittle function and that uses only a band of frequencies degenerating to zero. This method is implicitly defined by:

$$\hat{d} = \arg min\, d \left(log\overline{C(d)} - 2d \frac{1}{m} \sum_{j=1}^{m} log \lambda_j \right), \tag{11}$$

$$for\ d \in \left(-{}^{1}/_{2}, {}^{1}/_{2}\right); \quad \overline{C(d)} = \frac{1}{m} \sum_{j=1}^{m} I(\lambda_j) \lambda_j^{2d}, \quad \lambda_j = \frac{2\pi j}{T}, \frac{1}{m} + \frac{m}{T} \to 0,$$

where m is the bandwidth parameter, and I(λj) is the periodogram of the time series of interest. Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m}\left(\hat{d} - d_0\right) \to d \qquad N\left(0, {}^{1}/_{4}\right) \, as \; T \to \infty,$$

where d_o is the true value of d and with the only additional requirement that $m \to \infty$ slower than T.

4. EMPIRICAL RESULTS

The results for the *d* estimates are presented for both parametric and semi-parametric approaches. Beginning with the parametric approach as presented in Table 3, we report the estimated value of *d* for the three standard cases of: (i) no deterministic terms; (ii) an intercept, and (iii) an intercept and linear time trend. It is seen that the model without intercept and trend appears to be the best, as adjudged by the t-values of the coefficients, for five sectors namely Agriculture, Construction, Financial Services, Natural Resources and Oil & Gas, while the model with an intercept is the most efficient for the remaining five sectors. Therefore, these best models are re-presented in Table 4 with the intercept values of those sectors whose best model is the one with an intercept. The results reveal that the *d* estimates are significantly higher than 1 in all the sectors except Agriculture (1.0055) and Natural Resources (0.9725). Therefore, the random walk hypothesis which is established on the first-order integration property of a series is not rejected only for the Agriculture sector. The I(1) null hypothesis is rejected in favour of the alternative hypotheses of *d*<1 for the Natural Resources sector whose *d* estimates is lower than unitary and *d*>1 for the 10 sectors whose *d* estimates exceed unitary.

Table 3: Estimates based on the Parametric Method

Sector	No regressors	An intercept	A linear time trend
Agriculture	**1.0055 (0.0731)**	1.0054 (0.1041)	0.9937 (0.3269)
Conglomerate	1.1365 (0.0708)	**1.2788 (0.0901)**	1.2707 (0.0924)
Construction	**1.2162 (0.0797)**	1.2217 (0.0848)	1.2130 (0.0860)
Consumer Goods	1.1266 (0.0625)	**1.2891 (0.0864)**	1.2937 (0.0870)
Financial Services	**1.0577 (0.0679)**	1.0812 (0.0832)	1.0606 (0.0874)
Health	1.1319 (0.0758)	**1.1654 (0.0786)**	1.1392 (0.0818)
Industrial	1.1905 (0.0792)	**1.2169 (0.0806)**	1.2136 (0.0804)
Natural Resources	**0.9725 (0.0485)**	1.0000 (0.0000)	1.0000 (0.0000)
Oil and gas	**1.2734 (0.0893)**	1.2813 (0.0918)	1.2810 (0.0919)
Services	1.4429 (0.0905)	**1.3353 (0.0910)**	1.0000 (0.0000)

Values in parentheses are standard errors.

Table 4: Estimated coefficients in the selected models from Table 3

Sector	d-estimates	An intercept	A linear time trend
Agriculture	1.0055 (0.0731)	---------	---------
Conglomerate	**1.2788 (0.0901)**	-1.0748***	---------
Construction	**1.2162 (0.0797)**	---------	---------
Consumer Goods	**1.2891 (0.0864)**	-0.7644***	---------
Financial Services	**1.0577 (0.0679)**	---------	---------
Health	**1.1654 (0.0786)**	-1.1798*	---------
Industrial	**1.2169 (0.0806)**	-0.6471**	---------
Natural Resources	0.9725 (0.0485)	---------	---------
Oil and gas	**1.2734 (0.0893)**	---------	---------
Services	**1.3353 (0.0910)**	-0.5073*	---------

Values in parentheses are standard errors.

It can thus be deduced from the results that only the stock for the Agriculture sector is efficient following the definition of an efficient financial market as one whose prices exhibit random walk, hence cannot be subjected to accurate prediction or forecast. The results suggest inefficiency for the stock markets of the remaining sectors.

Table 5: Estimates based on the Semi-parametric Whittle Method

Sector	3	6	9	12	15	18
Agriculture	0.9319	0.9225	1.2559	1.1951	1.1382	1.0357
Conglomerate	1.2093	1.0890	1.0769	1.1611	1.2157	1.5418
Construction	1.0482	1.0924	0.9892	0.9548	0.9602	0.7580
Consumer Goods	1.0636	1.1099	1.2339	1.1616	1.1420	1.1018
Financial Services	0.9465	1.0540	1.0319	1.1147	1.3748	1.3748
Health	1.1417	1.0546	0.9019	0.9630	1.0913	1.3448
Industrial	1.1786	1.1193	1.0422	1.0463	1.0793	0.9339
Natural Resources	1.0676	0.9717	1.1195	1.2192	1.2759	0.9242
Oil and gas	1.1496	1.0364	0.9720	1.0551	0.7508	0.5512
Services	1.1622	1.1184	0.9307	0.9267	1.0473	1.2568

Using another approach, the *d* estimates are calculated using the semiparametric Whittle method. Presented in Table 5, the results indicate market inefficiency for most of the sectors across the chosen bandwidths. Expectedly, the *d* estimates change across the chosen bandwidths (see Table 5), but are largely above 1 in most cases, except Construction and Oil & Gas sectors. The reason for this is as a result of the sensitivity of the semi-parametric Whittle function to bandwidth choice. Usually, the technique performs better for series with large scope, hence the results could be bias (Caporale et al., 2018). Corroborating the findings of the parametric approach, the semi-parametric results presented in Table 5 convincingly supports stock market inefficiency for Conglomerate, Consumer Goods, Financial Services, and Industrial sectors by rejecting the random walk or I(1) hypothesis of the stock price series since the estimates are significantly higher than 1. For other sectors, although the estimates are also higher than 1 in majority of the chosen bandwidths, they are not convincing enough to conclude market inefficiency or otherwise.

Therefore, due to the sensitivity of the semi-parametric estimates to bandwidth choice, thus leading to a less conclusive report for some of the sectors, and consequently causing disagreement between the conclusion of the results of the parametric and non-parametric techniques in most of the sectors, we further employ the non-parametric technique to establish a stronger footing for our conclusion. The results of the non-parametric R/S analysis are shown in Table 6. Obviously, the R/S statistic gives a value greater than 0.5 for all the sectors, indicating persistence and absence of random walk in the stock prices.

Table 6: Estimates based on Non-parametric Method

Sector	R/S Statistic	Sector	R/S Statistic
Agriculture	0.5477	Health	0.5602
Conglomerate	0.5991	Industrial	0.5407
Construction	0.5512	Natural Resources	0.6726
Consumer Goods	0.6535	Oil and gas	0.5829
Financial Services	0.5350	Services	0.6135

Comparatively, it is discovered that the non-parametric results obviously align with the market inefficiency conclusion reached for nearly all the sectors, with the exemption of the Agriculture sector. While the parametric test concludes market efficiency for the Agriculture sector, the non-parametric test appears to show an R/S value that is a little above random walk. This notwithstanding shows that the Agriculture sector is still close to being efficient than being inefficient since the R/S value of 0.5477 can still be approximated to 0.5 which is the threshold for random walk. Therefore, the inefficiency of the stock of the other sectors apart from Agriculture implies that investors can strategically predict future prices of stock to make abnormal gains. On the other hand, traders in the Agriculture sector cannot make abnormal returns due to their inability to accurately forecast stock prices.

5. CONCLUSION

This paper examines the degree of persistence, and by implication market efficiency, of ten sectors in Nigeria using the parametric and semi-parametric techniques within the fractional integration long memory framework. The non-parametric R/S technique is further employed to bridge the gap between the differences between the results of the parametric and non-parametric approaches. Briefly, there is evidence that the Nigerian sectoral stock returns are largely inefficient. Only the Agriculture stock returns seems to be efficient.

While the results from the semi-parametric method appears to be less conclusive for most of the sectors as the estimated values of d are not convincingly higher or lower than 1 across the chosen bandwidths, the results from the parametric and non-parametric techniques align for a good number of sectors. The inconclusive nature of the semi-parametric results is due to the sensitivity of the technique to choice of bandwidth. Therefore, since market inefficiency or persistence means predictability, stock market traders can strategically predict the stock prices of the sectors, except Agriculture, to earn abnormal returns.

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