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Fractional integration and structural breaks in bank share prices in Nigeria☆

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Abstract

The paper employs both fractional integration and structural break techniques in studying the daily share prices structure of the banking sector in Nigeria. Our data span between 2001 and 2012, covers periods before and after the global financial crisis. The results obtained using both parametric and semiparametric methods indicate little evidence of mean reversion since most of the orders of integration are equal to or higher than 1. Long memory is found in the absolute and squared return series. The possibility of structural breaks is also taken into account and the results show a different number of breaks depending on the bank examined. In general, an increase in the degree of dependence across time is noticed, and the most common break took place in December 2008, probably being related with the world financial crisis affecting also the banking system in Nigeria.

JEL classification: C22; C55; C58; Y10

Keywords: Banks share prices; Fractional integration; Structural breaks; Nigeria

1. Introduction

The attainment and sustainability of economic growth requires a robust, stable and firmly anchored financial system since the banking sector provides funds for capital input from producers in other sectors of the economy as well as from the final consumers. Structural reforms in the banking sector in some developing countries have improved the health of the sector. These reforms have increased transparency and efficiency in the system and the effect of all such changes has been crucial on bank stock prices. The movement of prices in bank stocks is related to that of the entire stock market and this implies that bank stock returns are less influenced by bank-specific information (Roll, 1988).

In the 1990s, the Nigerian banking system was running smoothly and there was enough capital base in each bank to run the financial operations. At the end of 2004, the Nigerian banking sector was characterized by a high degree of fragmentation and low levels of financial intermediation. Motivated by this situation the Central Bank of Nigeria (CBN) carried out a reform which drastically increased the capital base of the banks from 2 billion Nigerian nairas to 25 billion Nigerian nairas, and this led to a remarkable reduction in the number of banks from 89 to 25, mainly by mergers and acquisitions in 2006 (Hesse, 2007). Mismanagement of funds and over-representation of share prices were experienced in some of the remaining 25 banks after the CBN reform in 2006, and once again following various mergers and acquisitions, the number of banks was further reduced to 21 (CBN, 2014).

Research on bank stock prices in the developed and emerging economies are few. This present work is the first to investigate this issue in Nigeria. Al-Zeaud (2011) fitted AutoRegressive Integrated Moving Average (ARIMA) models for weekly share prices of banks under the Amman Stock Exchange (ASE) between 2005 and 2010. Murari (2013) applied the CNX bank index of the National Stock Exchange of India (NSEI) on time series models and found the ARIMA (1, 0, 2) to be the appropriate model for predicting the volatility in the bank stock returns.

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Zahan and Kenett (2013) also fitted lower order ARIMA models for conventional and Islamic banks stock prices in Europe. A number of papers have applied variants of Autoregressive Conditional Heteroscedastic (ARCH) models on stock and share prices, while only a few considered the series on ARIMA models. Choice of the appropriate ARIMA or volatility models therefore depends on the stationarity property of the series.

This paper applies the long range dependence approach on the mean and variance series of the Nigerian banking share prices. The work further examines the possible structural breaks in the share prices over the years. The rest of the paper is structured as follows: Section 2 discusses the long range dependence approach as well as the presence of structural breaks in the context of fractional integration. Section 3 presents the data and the empirical results, while Section 4 gives some concluding remarks.

2. Methodology

This paper focuses on the issue of long range dependence or long memory and in particular uses fractional integration or $I(d)$ models. An $I(d)$ process can be defined as follows: let u_t be an integrated of order 0 ($I(0)$) process, defined as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. In this context, x_t is said to be integrated of order d, and denoted by $x_t \approx I(d)$ if it can be expressed as follows:

$$(1-L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{1}$$

where L is the lag operator ($Lx_t = x_{t-1}$) and d can be any real number. Using a Binomial expansion on the polynomial in L in (1) we obtain that

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j$$
$$= 1 - dL + \frac{d(d-1)}{2} L^2 - \cdots,$$

and thus

$$(1-L)^d x_t = x_t - d x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \cdots$$

In this context, d plays a crucial role, since it will be an indicator of the degree of dependence of the series. Thus, the higher the value of d is, the higher the level of association will be between the observations. Processes with $d > 0$ in Eq. (1) display the property of "*long memory*", so-named because of the strong degree of association between observations which are very distant in time. They are also characterized because the autocorrelations decay hyperbolically slow and the spectral density function is unbounded at the origin.

The methodology employed in the paper to estimate the fractional differencing parameter is based on both parametric and semiparametric methods. In the parametric approach we use the Whittle function in the frequency domain, assuming different models for the disturbance errors, while a "local" Whittle estimate is used in the semiparametric case. The issue of structural breaks is also taken into account, and for this purpose, we use a methodology devised by Gil-Alana (2008) that allows fractional differencing parameters to be estimated in the context of breaks, with the number of breaks and the break dates being endogenously determined by the model itself.

3. Data and empirical results

We use daily data of share prices of banks in Nigeria for the 12 highly capitalized commercial banks in the country listed on the platform of the Nigerian Stock Exchange (NSE). These are the Access Bank, the Diamond Bank, Fidelity Bank, First Bank, First City Monument Bank (FCMB), Guaranty Trust Bank (GTB), Sterling Bank, United Bank, Union Bank, Unity Bank, Wema Bank and Zenith Bank, for the time period January 2nd, 2001 to December 30th, 2012 and no adjustment was made for non-trading days (weekends and holidays). Different episodes of banks re-capitalization took place during the sample data period, some banks were stopped from operating by the CBN, while others merged with those with stronger financial backing. Based on these reasons, and for consistency in the sample data points, we resolved to use the banks that have been listed on the platform of the NSE from as far back as 2001. The time plots representing the share prices of these banks over the time periods are presented in Fig. 1.

Notice that for six of the series (Diamond, Fidelity, FCMB, Sterling, Unity and Zenith) the values remain constant during the first four years, which might affect the results presented, however for the remaining series, the values keep moving from the very beginning of the sample. In general, we observe in the 12 series an increase in the values starting at April 2006 and lasting for a couple of years, the values decrease abruptly around May 2008, coinciding with the major financial crisis affecting countries all over the world.

The descriptive measures on the shares prices of these banks are presented in Table 1. We observed that First Bank has the highest average share price (₦25.02), while Unity Bank has an average of ₦2.34 as its share price. The average share prices for each of the banks are about one-third of the highest prices observed for banks in Nigeria just before the global financial crisis in early 2009.

The first thing we do in this section is to estimate the fractional differencing parameter for each series. We use the log-transformed data such that the first differences of the logged prices are the returns series. First, we employ a parametric Whittle approach (Dahlhaus, 1989) using different assumptions for the error term. In particular, we employ the following model,

$$y_t = \alpha + \beta t + x_t; \quad (1-L)^d x_t = u_t; \quad t = 1, 2, \ldots, \tag{1}$$

where y_t is the observed time series (the log-prices) and x_t is supposed to be $I(d)$ where d, the degree of integration, is a real parameter to be estimated from the data. Given the parametric nature of the method, we need to impose a modelling assumption for the error term u_t in (1). First, we will suppose u_t is uncorrelated (white noise); then an AR(1) process is assumed, and finally, the exponential spectral model of Bloomfield (1973)

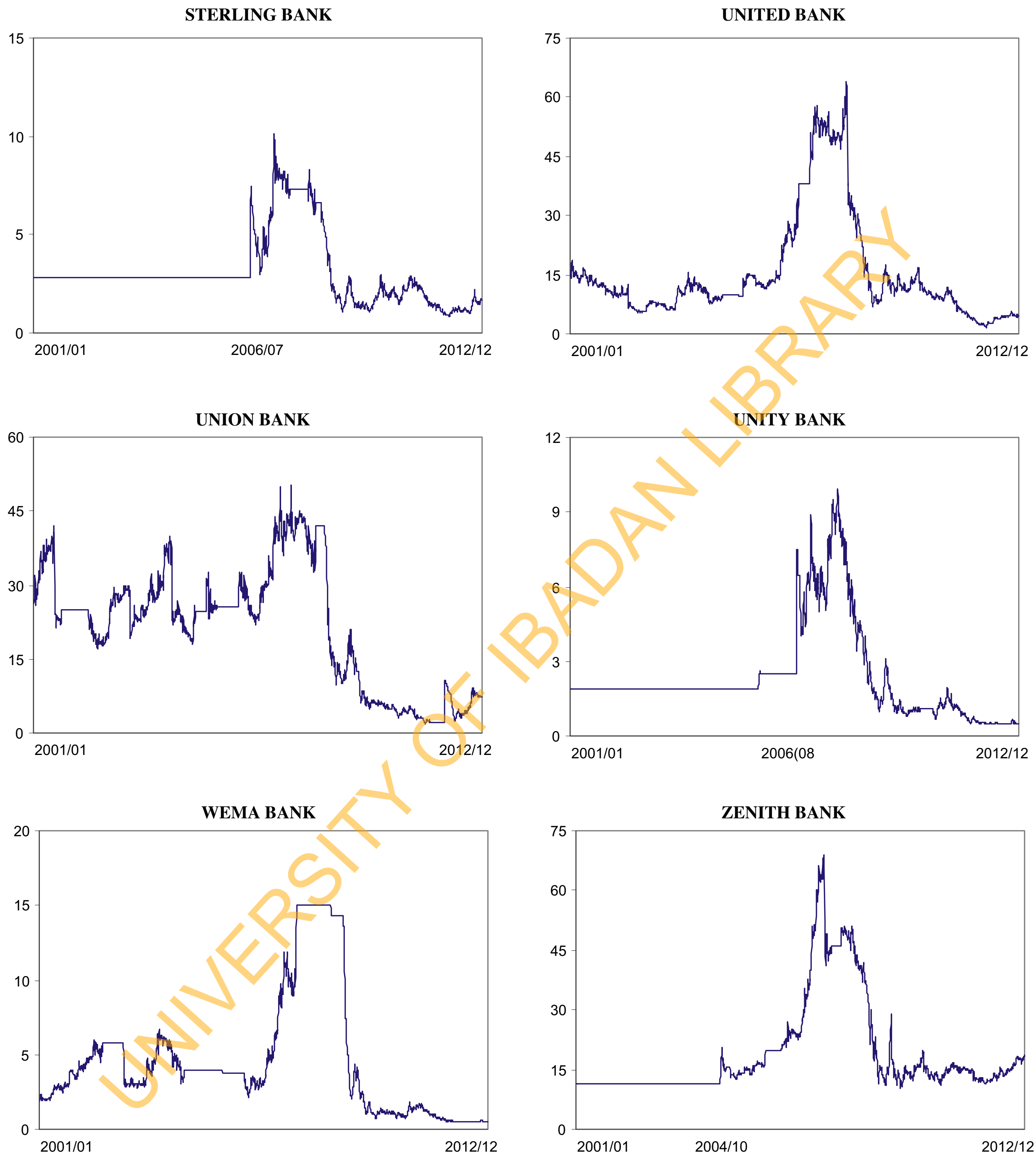

Fig. 1. Original time series.

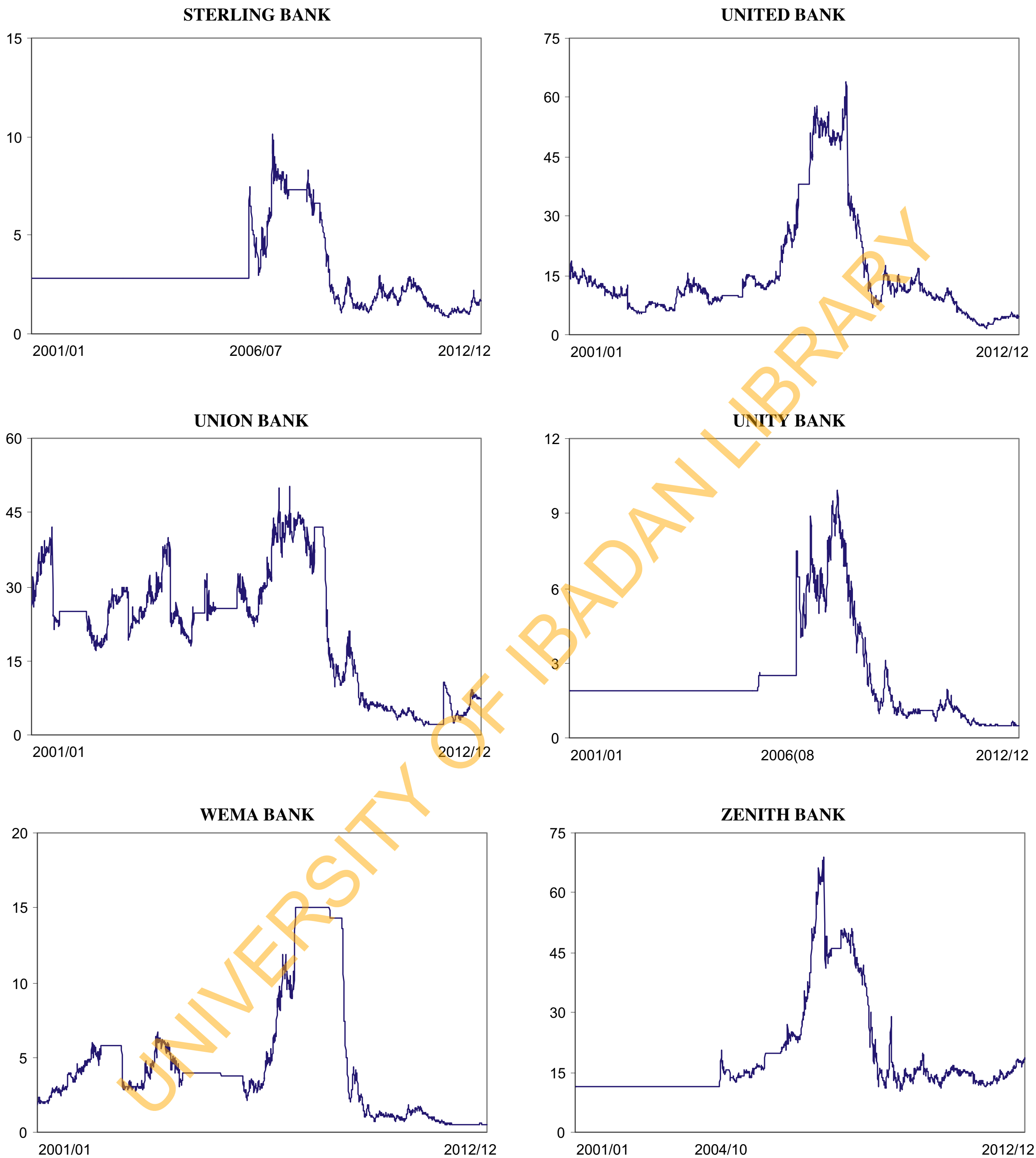

Fig. 1. (*Continued*)

Table 1
Descriptive measures.

Banks	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis
Access	6.587	4.880	25.500	1.000	5.579	1.517	4.703
Diamond	7.963	6.950	23.450	1.920	4.101	1.851	6.350
Fidelity	3.740	2.940	13.000	1.130	2.689	2.193	6.531
First	25.024	23.700	72.760	7.950	11.095	0.791	3.369
FCMB	6.331	4.390	21.600	2.320	4.216	1.893	5.574
GTB	14.738	13.660	40.000	4.170	8.066	1.076	3.720
Sterling	3.073	2.800	10.100	0.800	1.774	1.612	4.870
UBA	15.313	11.020	63.940	1.640	13.192	1.908	5.702
Union	21.386	24.510	50.330	1.960	12.312	−0.035	2.011
Unity	2.344	1.900	9.950	0.500	1.886	1.970	6.331
Wema	4.550	3.740	15.000	0.500	4.134	1.519	4.365
Zenith	18.956	14.010	68.970	10.110	12.124	2.016	6.106

FCMB – First City Monument Bank; GTB – Guaranty Trust Bank; UBA – United Bank.

is taken into account. The latter is a non-parametric approach of modelling the $I(0)$ error term that produces autocorrelations decaying exponentially as in the AR case.[1]

We present the results for the three standard cases examined in the literature, that is, the case of no deterministic terms in the undifferenced regression (i.e., $\alpha = \beta = 0$ in (1)), an intercept (α unknown and $\beta = 0$), and an intercept with a linear time trend (α and β unknown). Table 2(i) focuses on the case of white noise disturbances; Table 2(ii) displays the results for AR(1) disturbances, while Table 2(iii) refers to the exponential spectral model of Bloomfield (1973).

Starting with the results based on white noise disturbances (in Table 2(i)) we observe that only for FCMB do we find some evidence of mean reversion, since the $I(1)$ hypothesis is rejected in favour of $d < 1$ for the cases of an intercept and a linear time trend. There is another bank (First) where the unit root null (i.e., $d = 1$) cannot be rejected, while for the remaining banks the results suggest orders of integration significantly above 1, ranging from 1.06 (GTB) to 1.21 (Diamond and Wema banks).

The above results, however, might be biased due to the lack of autocorrelation for the error term. Thus, in what follows, we allow for autocorrelation, first using a simple AR(1) structure for the disturbances. The results are displayed in Table 2(ii), and the orders of integration are slightly smaller than in the previous case of uncorrelated errors. Thus, we observe some evidence of mean reversion (i.e., $d < 1$ in First and GTB) and evidence of unit roots ($d = 1$) in another group formed by seven banks (Access, Diamond, Fidelity, Sterling, United, Union and Zenith). For the remaining three banks (FCMB, Unity and Wema) the orders of integration are significantly higher than 1. Finally, we employ a more general autocorrelated specification for the error term based on the model of Bloomfield (1973) and the results, displayed in Table 2(iii), are very similar to the case of AR(1) errors: mean reversion ($d < 1$) is obtained for First Bank and GTB; unit roots ($d = 1$) for Access, Fidelity, Sterling, United, Union and Zenith banks; and $I(d)$ with $d > 1$ for Diamond, FCMB, Unity and Wema banks.

To check for robustness, we also employed a semiparametric estimation approach for the differencing parameter. In this context, no functional form is imposed on the $I(0)$ error term u_t. In particular, we use a "local" Whittle approach suggested by Robinson (1995) and improved later by Velasco (1999), Velasco and Robinson (2000), Phillips and Shimotsu (2004) and Abadir et al. (2007) among many others.

Given the nonstationary nature of the series examined, the results have been obtained based on the first differenced data, then adding 1 to obtain the proper orders of integration of the series. We observe in Table 3 that for Fidelity and FCMB most of the estimates are above 0 implying orders of integration in the original series above 1. Some evidence of explosive behaviour is also observed in GTB, United and Access banks for some bandwidth numbers, while for the remaining series most of the values are within the $I(0)$ interval ($I(1)$ in the original series). No evidence of mean reversion is obtained in any single case. Table 4 produces some summary statistics of the results presented so far. We observe that across the different methods presented the only evidence of mean reversion is obtained for FCMB in the case of white noise errors, and for First Bank and GTB with autocorrelated disturbances.

Next we focus on the data starting in January 2005. In doing so, we eliminate the potential bias created by the existence of constant values at the beginning of various series. Table 5(i) displays the Whittle parameter estimates of d for the case of white noise disturbances, while Table 5(ii) and (iii) refers respectively to the cases of AR(1) and Bloomfield disturbances. If u_t is white noise, mean reversion only takes place in the case of the FCMB with an intercept and with an intercept and a linear trend, and allowing for autocorrelation, First Bank and GTB are the only ones with estimates of d which are statistically below 1. With the semiparametric approach (Table 6), all the estimated values of d are equal to or higher than 0 in the first differenced (return) series. Table 7 summarizes the results reported across Tables 5 and 6, and the results are fairly similar to those reported in Table 4 for the complete dataset. As a final remark we can mention that the Efficient Market Hypothesis (EMH) is decisively rejected in all except one single series corresponding to First Bank in the results reported in Tables 2(i) and 5(i). Note that this hypothesis is consistent with the existence of a random

[1] See Gil-Alana (2004) for a justification of the use of the model of Bloomfield (1973) in the context of fractional integration.

Table 2
Estimates of d based using a parametric approach.

Banks	No regressors	An intercept	A linear time trend
(i) White noise disturbances			
Access	1.10 (1.07, 1.12)	1.10 (1.08, 1.13)	1.10 (1.08, 1.13)
Diamond	1.07 (1.04, 1.10)	1.21 (1.18, 1.25)	1.21 (1.18, 1.25)
Fidelity	1.10 (1.08, 1.14)	1.20 (1.16, 1.24)	1.20 (1.16, 1.24)
First	1.00 (0.98, 1.03)	1.01 (0.98, 1.04)	1.01 (0.98, 1.04)
FCMB	0.99 (0.97, 1.01)	**0.97 (0.95, 0.99)**	**0.97 (0.95, 0.99)**
GTB	1.05 (1.03, 1.08)	1.06 (1.03, 1.09)	1.06 (1.03, 1.09)
Sterling	1.10 (1.07, 1.13)	1.14 (1.11, 1.18)	1.14 (1.11, 1.18)
United	1.04 (1.00, 1.07)	1.13 (1.10, 1.16)	1.13 (1.10, 1.16)
Union	1.02 (1.00, 1.05)	1.07 (1.04, 1.10)	1.07 (1.04, 1.10)
Unity	1.08 (1.05, 1.10)	1.09 (1.06, 1.11)	1.09 (1.06, 1.11)
Wema	1.20 (1.17, 1.23)	1.21 (1.18, 1.24)	1.21 (1.18, 1.24)
Zenith	1.03 (1.00, 1.06)	1.17 (1.13, 1.20)	1.17 (1.13, 1.20)
(ii) AR(1) disturbances			
Access	1.01 (0.96, 1.06)	1.02 (0.97, 1.06)	1.02 (0.97, 1.06)
Diamond	xxx	1.00 (0.94, 1.05)	1.00 (0.94, 1.05)
Fidelity	xxx	1.00 (0.96, 1.04)	1.00 (0.96, 1.04)
First	xxx	**0.89 (0.85, 0.94)**	**0.89 (0.85, 0.94)**
FCMB	1.13 (1.07, 1.19)	1.07 (1.04, 1.11)	1.07 (1.04, 1.11)
GTB	xxx	**0.92 (0.87, 0.97)**	**0.92 (0.88, 0.97)**
Sterling	xxx	1.01 (0.96, 1.07)	1.01 (0.96, 1.07)
United	xxx	0.98 (0.93, 1.04)	0.98 (0.93, 1.04)
Union	xxx	1.00 (0.95, 1.05)	1.00 (0.95, 1.05)
Unity	1.05 (0.98, 1.11)	1.06 (1.00, 1.12)	1.06 (1.00, 1.12)
Wema	1.08 (1.01, 1.15)	1.09 (1.04, 1.15)	1.09 (1.04, 1.15)
Zenith	xxx	0.96 (0.91, 1.01)	0.96 (0.91, 1.01)
(iii) Bloomfield disturbances			
Access	1.03 (0.99, 1.07)	1.02 (0.99, 1.07)	1.02 (0.99, 1.07)
Diamond	1.03 (0.99, 1.07)	1.06 (1.02, 1.10)	1.06 (1.02, 1.10)
Fidelity	1.03 (1.00, 1.07)	1.03 (0.99, 1.07)	1.03 (0.99, 1.07)
First	0.98 (0.94, 1.02)	**0.91 (0.87, 0.95)**	**0.91 (0.87, 0.95)**
FCMB	1.05 (1.01, 1.10)	1.09 (1.05, 1.13)	1.09 (1.05, 1.13)
GTB	0.99 (0.95, 1.02)	**0.94 (0.90, 0.99)**	**0.94 (0.90, 0.99)**
Sterling	1.03 (0.99, 1.08)	1.04 (0.99, 1.09)	1.04 (0.99, 1.09)
United	1.01 (0.97, 1.06)	1.03 (0.98, 1.06)	1.03 (0.98, 1.06)
Union	1.01 (0.97, 1.06)	1.02 (0.97, 1.05)	1.02 (0.97, 1.05)
Unity	1.05 (1.00, 1.10)	1.05 (1.01, 1.11)	1.05 (1.01, 1.11)
Wema	1.120 (1.07, 1.15)	1.11 (1.07, 1.17)	1.11 (1.07, 1.17)
Zenith	1.00 (0.96, 1.04)	1.00 (0.96, 1.04)	1.00 (0.96, 1.04)

In bold, evidence of mean reversion ($d < 1$) at the 5% level. xxx means that convergence was not achieved.

Table 3
Estimates of d based on semiparametric methods (return series).

M	20	30	40	50	60	70	80	90
Access	0.143	**0.150**	0.129	0.108	0.036	0.032	0.040	0.056
Diamond	0.143	0.091	0.084	0.057	0.053	0.056	0.081	0.077
Fidelity	**0.274**	**0.170**	**0.214**	**0.267**	**0.160**	**0.136**	**0.166**	**0.141**
First	−0.028	−0.029	−0.032	−0.036	−0.018	−0.003	−0.006	−0.015
FCMB	0.025	0.144	**0.246**	**0.252**	**0.226**	**0.198**	**0.098**	**0.124**
GTB	0.131	0.116	**0.262**	**0.160**	**0.132**	0.096	0.070	0.046
Sterling	−0.049	0.000	−0.019	−0.057	−0.003	0.013	−0.037	−0.012
United	0.127	**0.172**	**0.197**	**0.149**	0.100	0.057	0.046	0.068
Union	−0.156	−0.088	−0.120	−0.096	−0.039	−0.017	−0.073	−0.052
Unity	0.114	0.069	−0.028	−0.036	−0.087	−0.066	−0.054	−0.044
Wema	0.133	0.077	0.057	0.074	0.044	0.090	0.080	**0.111**
Zenith	0.078	**0.158**	0.011	0.0451	0.100	0.034	−0.032	−0.013
95% low	−0.184	−0.150	−0.130	−0.116	−0.106	−0.098	−0.091	−0.086
95% up	0.184	0.150	0.130	0.116	0.106	0.098	0.091	0.086

In bold, evidence of explosive behaviour ($d > 1$) at the 5% level.

Table 4
Summary statistics about the degree of integration of the series.

	Mean reversion ($d > 1$)	Unit roots ($d = 1$)	Explosive behaviour ($d > 1$)
White noise disturbances	FCMB	First	Access, Diamond, Fidelity, GTB, Sterling, United, Union, Unity, Wema, Zenith
AR(1) disturbances	First, GTB	Access, Diamond, Fidelity, Sterling, United, Union, Zenith	FCMB, Unity, Wema
Bloomfield (1973) type disturbances	First, GTB	Access, Fidelity, Sterling, United, Union, Zentith	Diamond, FCMB, Unity, Wema
Non-parametric approach ($m = 50$)		Access, Diamond, First, Sterling, Union, Unity	Fidelity, FCMB, GTB, United

walk process for the log-prices series, and the $I(1)$ hypothesis with white noise errors is rejected in all cases in the tables except for the First Bank.

The following table focuses on the volatility processes measured in terms of the absolute and the squared return series. These two measures have been widely employed as proxies for the volatility of the series. Thus, for example, absolute returns have been employed among others by Ding et al. (1993), Granger and Ding (1996), Bollerslev and Wright (2000), Gil-Alana (2005), Sibbertsen (2004) and Cotter (2005), whereas squared returns were used in Lobato and Savin (1998), Gil-Alana (2003) and Cotter (2005).

Table 5
Estimates of d based on white noise disturbances (data starting in 2005).

Banks	No regressors	An intercept	A linear time trend
(i) White noise disturbances			
Access	1.07 (1.04, 1.10)	1.12 (1.09, 1.16)	1.12 (1.09, 1.16)
Diamond	1.07 (1.03, 1.10)	1.21 (1.17, 1.25)	1.21 (1.17, 1.25)
Fidelity	1.10 (1.07, 1.14)	1.20 (1.16, 1.24)	1.20 (1.16, 1.24)
First	1.00 (0.97, 1.03)	1.00 (0.97, 1.04)	1.00 (0.97, 1.04)
FCMB	0.99 (0.96, 1.02)	**0.96 (0.94, 0.99)**	**0.96 (0.94, 0.99)**
GTB	1.01 (0.97, 1.05)	1.04 (1.00, 1.08)	1.04 (1.00, 1.08)
Sterling	1.10 (1.06, 1.13)	1.14 (1.10, 1.18)	1.14 (1.10, 1.18)
United	1.04 (1.01, 1.08)	1.16 (1.12, 1.20)	1.16 (1.12, 1.20)
Union	1.03 (1.00, 1.06)	1.07 (1.03, 1.10)	1.07 (1.03, 1.10)
Unity	1.08 (1.04, 1.11)	1.09 (1.05, 1.12)	1.09 (1.05, 1.12)
Wema	1.14 (1.10, 1.17)	1.28 (1.24, 1.32)	1.28 (1.24, 1.32)
Zenith	1.02 (0.99, 1.05)	1.15 (1.11, 1.20)	1.15 (1.11, 1.20)
(ii) AR(1) disturbances			
Access	xxx	1.03 (0.98, 1.08)	1.03 (0.98, 1.08)
Diamond	xxx	1.00 (0.93, 1.06)	1.00 (0.93, 1.06)
Fidelity	xxx	1.00 (0.95, 1.06)	1.00 (0.95, 1.06)
First	xxx	**0.90 (0.85, 0.96)**	**0.90 (0.85, 0.96)**
FCMB	1.16 (1.07, 1.23)	1.06 (1.02, 1.11)	1.06 (1.02, 1.11)
GTB	xxx	**0.92 (0.87, 0.98)**	**0.92 (0.87, 0.98)**
Sterling	xxx	1.01 (0.95, 1.08)	1.01 (0.95, 1.08)
United	xxx	1.00 (0.95, 1.07)	1.00 (0.95, 1.07)
Union	xxx	1.01 (0.95, 1.07)	1.01 (0.95, 1.07)
Unity	1.05 (0.97, 1.12)	1.06 (0.99, 1.13)	1.06 (0.99, 1.13)
Wema	xxx	1.13 (1.06, 1.20)	1.13 (1.06, 1.21)
Zenith	xxx	0.95 (0.90, 1.01)	0.95 (0.90, 1.01)
(iii) Bloomfield disturbances			
Access	1.03 (0.99, 1.07)	1.04 (0.99, 1.09)	1.04 (0.99, 1.09)
Diamond	1.03 (0.98, 1.08)	1.06 (1.01, 1.11)	1.06 (1.01, 1.11)
Fidelity	1.03 (1.01, 1.08)	1.03 (0.99, 1.08)	1.03 (0.99, 1.08)
First	0.98 (0.95, 1.03)	**0.93 (0.88, 0.97)**	**0.93 (0.88, 0.97)**
FCMB	1.04 (0.99, 1.08)	1.07 (1.02, 1.12)	1.07 (1.02, 1.12)
GTB	0.99 (0.94, 1.04)	**0.94 (0.90, 0.99)**	**0.94 (0.90, 0.99)**
Sterling	1.03 (0.98, 1.09)	1.04 (0.99, 1.10)	1.04 (0.99, 1.10)
United	1.01 (0.97, 1.06)	1.04 (0.99, 1.10)	1.04 (0.99, 1.10)
Union	1.00 (0.96, 1.00)	1.02 (0.97, 1.08)	1.02 (0.97, 1.08)
Unity	1.05 (0.99, 1.11)	1.05 (1.00, 1.12)	1.05 (1.00, 1.12)
Wema	1.10 (1.05, 1.16)	1.17 (1.11, 1.24)	1.17 (1.11, 1.24)
Zenith	1.00 (0.96, 1.04)	0.99 (0.94, 1.05)	0.99 (0.94, 1.05)

In bold, evidence of mean reversion ($d < 1$) at the 5% level.

Table 6
Estimates of d based on semiparametric methods (data starting in 2005).

M	20	30	40	50	60	70	80	90
Access	**0.228**	**0.200**	0.095	0.095	0.093	0.072	0.059	0.021
Diamond	0.074	0.080	0.061	0.090	0.088	0.041	0.021	0.040
Fidelity	0.179	**0.273**	**0.171**	**0.157**	**0.151**	**0.158**	0.088	0.070
First	0.057	−0.010	−0.008	−0.004	0.001	−0.014	−0.086	−0.081
FCMB	**0.187**	**0.352**	**0.251**	**0.144**	**0.136**	**0.185**	**0.138**	**0.144**
GTB	0.113	**0.228**	0.105	0.042	0.034	0.017	−0.082	−0.073
Sterling	0.019	−0.027	0.013	−0.001	−0.001	0.024	0.008	0.036
United	**0.192**	**0.227**	**0.146**	0.085	**0.113**	0.069	0.026	0.031
Union	−0.054	−0.055	−0.018	−0.060	−0.048	−0.022	−0.037	−0.014
Unity	0.060	−0.025	−0.092	−0.063	−0.039	−0.041	−0.061	−0.099
Wema	0.159	0.094	0.058	0.078	0.035	0.062	0.085	**0.102**
Zenith	0.090	**0.156**	0.021	0.051	0.052	0.025	−0.051	−0.037
95% low	−0.184	−0.150	−0.130	−0.116	−0.106	−0.098	−0.091	−0.086
95% up	0.184	0.150	0.130	0.116	0.106	0.098	0.091	0.086

Table 7
Summary statistics with data starting in 2005.

	Mean reversion ($d > 1$)	Unit roots ($d = 1$)	Explosive behaviour ($d > 1$)
White noise disturbances	FCMB	First	Access, Diamond, Fidelity, GTB, Sterling, United, Union, Unity, Wema, Zenith
AR(1) disturbances	First, GTB	Access, Diamond, Fidelity, Sterling, United, Union, Unity, Zenith	FCMB, Wema
Bloomfield (1973) disturbances	First, GTB	Access, Fidelity, Sterling, United, Union, Zenith	Diamond, FCMB, Unity, Wema
Non-parametric approach ($m = 50$)		Access, Diamond, First, GTB, United, Sterling, Union, Unity	Fidelity, FCMB

Table 8
Estimates of d for the volatility processes (data starting in 2005).

Banks	No regressors	An intercept	A linear time trend
(i) Absolute returns			
Access	**0.20 (0.18, 0.23)**	**0.22 (0.19, 0.24)**	**0.21 (0.18, 0.24)**
Diamond	**0.30 (0.27, 0.33)**	**0.31 (0.28, 0.34)**	**0.30 (0.28, 0.33)**
Fidelity	**0.31 (0.28, 0.34)**	**0.32 (0.29, 0.35)**	**0.31 (0.29, 0.34)**
First	**0.24 (0.21, 0.27)**	**0.24 (0.21, 0.27)**	**0.24 (0.21, 0.27)**
FCMB	**0.35 (0.31, 0.40)**	**0.35 (0.31, 0.40)**	**0.35 (0.31, 0.40)**
GTB	**0.24 (0.21, 0.27)**	**0.23 (0.20, 0.26)**	**0.23 (0.20, 0.26)**
Sterling	**0.22 (0.20, 0.24)**	**0.23 (0.21, 0.25)**	**0.22 (0.20, 0.24)**
United	**0.23 (0.20, 0.26)**	**0.24 (0.21, 0.27)**	**0.23 (0.21, 0.26)**
Union	**0.12 (0.09, 0.14)**	**0.13 (0.10, 0.15)**	**0.11 (0.08, 0.14)**
Unity	**0.20 (0.18, 0.22)**	**0.20 (0.18, 0.23)**	**0.20 (0.18, 0.22)**
Wema	**0.35 (0.33, 0.37)**	**0.36 (0.33, 0.38)**	**0.35 (0.33, 0.38)**
Zenith	**0.24 (0.21, 0.26)**	**0.24 (0.22, 0.26)**	**0.24 (0.22, 0.26)**
(ii) Squared returns			
Access	0.00 (−0.03, 0.04)	0.00 (−0.03, 0.04)	0.00 (−0.03, 0.04)
Diamond	**0.25 (0.22, 0.28)**	**0.25 (0.23, 0.28)**	**0.25 (0.22, 0.28)**
Fidelity	**0.26 (0.23, 0.29)**	**0.27 (0.24, 0.30)**	**0.26 (0.23, 0.29)**
First	**0.03 (0.00, 0.07)**	**0.03 (0.00, 0.07)**	**0.03 (0.00, 0.07)**
FCMB	**0.40 (0.34, 0.47)**	**0.40 (0.34, 0.47)**	**0.40 (0.34, 0.47)**
GTB	**0.11 (0.08, 0.14)**	**0.11 (0.08, 0.14)**	**0.11 (0.08, 0.14)**
Sterling	0.01 (−0.03, 0.04)	0.00 (−0.03, 0.04)	0.01 (−0.03, 0.04)
United	**0.03 (0.00, 0.06)**	**0.03 (0.00, 0.06)**	**0.03 (0.00, 0.06)**
Union	0.00 (−0.03, 0.03)	0.00 (−0.03, 0.03)	0.00 (−0.04, 0.03)
Unity	0.00 (−0.03, 0.03)	0.00 (−0.03, 0.03)	0.00 (−0.03, 0.03)
Wema	**0.28 (0.26, 0.31)**	**0.29 (0.27, 0.31)**	**0.29 (0.26, 0.31)**
Zenith	**0.05 (0.02, 0.07)**	**0.05 (0.02, 0.07)**	**0.05 (0.02, 0.07)**

In bold, evidence of mean reversion at the 5% level.

Table 9
Number of breaks and break dates for each series.

Banks	NB	1st subs.	2nd subs.	3rd subs.	4th subs.	5th subs.
Access	3	Jan-05–Oct-06	Nov-06–Dec-07	Jan-08–Dec-08	Jan-09–Dec-12	–
Diamond	3	Jan-05–Oct-06	Nov-06–Dec-07	Jan-08–Dec-08	Jan-09–Dec-12	–
Fidelity	3	Jan-05–Oct-06	Nov-06–Dec-07	Jan-08–Mar-09	Apr-09–Dec-12	–
First	2	Jan-05–Jan-08	Feb-08–Dec-08	Jan-09–Dec-12	–	–
FCMB	3	Jan-05–Oct-06	Nov-06–Dec-07	Jan-08–Dec-08	Jan-09–Dec-12	–
GTB	3	Jan-05–Oct-06	Nov-06–Jan-08	Feb-08–Dec-08	Jan-09–Dec-12	–
Sterling	3	Jan-05–Dec-06	Jan-07–Mar-08	Apr-08–Dec-08	Jan-09–Dec-12	–
United	2	Jan-05–Apr-08	May08–Dec-08	Jan-09–Dec-12	–	–
Union	2	Jan-05–Oct-07	Nov-07–Dec-08	Jan-09–Dec-12	–	–
Unity	2	Jan-05–Dec-06	Jan-07–Feb-09	Mar-09–Dec-12	–	–
Wema	4	Jan-05–Dec-06	Jan-07–Oct-07	Nov-07–Dec-08	Jan-09–Mar-09	Mar-09–Dec-12
Zenith	2	Jan-05–Jul-07	Aug-07–Dec-08	Jan-09–Dec-12	–	–

Table 10
Estimates of the differencing parameters for each subsample.

Banks	1st subs.	2nd subs.	3rd subs.	4th subs.	5th subs.
Access	1.04 (0.96, 1.13)	1.20 (1.13, 1.29)	1.24 (1.14, 1.37)	1.10 (1.05, 1.16)	–
Diamond	1.20 (1.13, 1.18)	1.25 (1.16, 1.37)	1.29 (1.18, 1.41)	1.17 (1.12, 1.24)	–
Fidelity	1.26 (1.16, 1.38)	1.34 (1.23, 1.47)	1.26 (1.18, 1.32)	1.16 (1.10, 1.23)	–
First	0.98 (0.92, 1.04)	1.34 (1.21, 1.49)	**0.93 (0.89, 0.97)**	–	–
FCMB	1.07 (0.99, 1.15)	1.19 (1.11, 1.29)	1.17 (1.09, 1.28)	**0.87 (0.84, 0.91)**	–
GTB	1.07 (0.98, 1.17)	1.09 (0.99, 1.19)	1.32 (1.19, 1.47)	**0.91 (0.86, 0.96)**	–
Sterling	1.10 (1.04, 1.16)	1.29 (1.19, 1.41)	1.12 (1.02, 1.26)	1.13 (1.08, 1.19)	–
United	1.08 (1.02, 1.15)	1.21 (1.10, 1.35)	1.16 (1.10, 1.22)	–	–
Union	1.05 (0.97, 1.13)	1.19 (1.10, 1.30)	1.06 (1.02, 1.11)	–	–
Unity	1.31 (1.26, 1.37)	1.22 (1.15, 1.29)	1.09 (1.04, 1.14)	–	–
Wema	1.33 (1.23 1.44)	1.35 (1.22, 1.53)	1.85 (1.73, 1.98)	1.08 (0.94, 1.33)	1.24 (1.18, 1.29)
Zenith	1.15 (1.06, 1.24)	1.33 (1.24, 1.43)	1.10 (1.04, 1.15)	–	–

In bold, evidence of mean reversion at the 5% level.

Table 8(i) displays the estimates of d in the absolute returns, while Table 8(ii) focuses on the squared returns. In the former case, we see that all the estimates are statistically significantly positive implying long memory behaviour, the values ranging between 0.11 (Union Bank with a linear time trend) and 0.36 (Wema Bank with an intercept). For the squared returns, long memory is also found in the majority of the cases, though the hypothesis of short memory behaviour cannot be rejected in the cases of Sterling, Union and Unity banks. This evidence of long memory in the volatility processes is consistent with what is found in other more developed financial markets (see Gil-Alana et al., 2014).

On the other hand, some authors have suggested that fractional integration may be an artificial artefact generated by the presence of breaks in the data that have not been taken into account.[2] Thus, in what follows, we use a methodology suggested by Gil-Alana (2008) that allows us to test the presence of breaks in the context of fractional integration. In particular, using this method we can endogenously determine the number of structural breaks along with the break dates, and the fractional differencing parameters for each subsample separately. The estimated number of breaks and the breaks dates for each series are displayed in Table 9. It can be observed that four breaks are found in the case of the Wema bank; three breaks for six banks (Access, Diamonds, Fidelity, FCMB, GTB and Sterling) and two breaks in the remaining banks (First, United, Union, Unity and Zenith). This heterogeneity in the number of breaks across banks also takes place when looking at the break dates, though a common break date in almost all banks is December 2008. Other frequent break dates in the banks are October 2006 and December 2007. The break in December 2008 is a result of the global financial crisis. Although this crisis started in the US in August 2007 and it began to affect the Nigerian capital market in February 2008, it did not begin to affect the banking industry in the country until between April and May 2008. In this period investors started selling their bank shares leading to a drastic fall in the share prices. The break in October 2006 is a result of the merging and consolidations of banks around that time. This affected the capitalizations of banks, and raised bank share prices for some time.

Table 10 displays the estimated fractional differencing parameters for each subsample. Among them we observe only very few cases of mean reversion. In particular, estimates of d statistically below 1 are only obtained in the third subsample of the First Bank and in the fourth subsample for FCMB and GTB. If we focus on the estimates of d for each subsample using the Whittle semiparametric method, the results are displayed in

[2] See among others Cheung (1993), Diebold and Inoue (2001), Giraitis et al. (2001), Mikosch and Starica (2004) and Granger and Hyung (2004).

Table 11
Estimates of *d* based on semiparametric methods (data starting in 2005) (RETURNS).

M	Subs.	5	10	15	20	30	40	50
Access	1st	0.375	0.005	−0.122	**−0.184**	**−0.221**	**−0.143**	**−0.120**
	2nd	−0.001	0.174	0.125	0.118	0.144	0.177	0.199
	3rd	−0.103	**−0.276**	−0.113	−0.079	−0.014	0.049	0.092
	4th	0.036	0.020	−0.024	−0.030	0.058	0.038	0.009
Diamond	1st	−0.198	0.122	**−0.288**	**−0.188**	−0.028	0.077	0.071
	2nd	−0.142	0.028	0.363	0.378	0.115	0.069	0.107
	3rd	−0.028	**−0.372**	**−0.293**	**−0.283**	−0.146	0.023	0.215
	4th	0.455	0.203	0.052	0.053	0.119	0.138	0.112
Fidelity	1st	0.500	0.202	−0.151	**−0.226**	**−0.248**	**−0.219**	**−0.164**
	2nd	0.430	0.279	0.045	0.044	0.018	0.065	0.128
	3rd	−0.282	−0.185	0.015	0.007	0.028	0.017	0.058
	4th	−0.142	−0.139	0.042	0.087	0.150	0.125	0.107
First	1st	−0.321	0.040	−0.151	−0.064	**−0.168**	**−0.176**	**−0.149**
	2nd	−0.226	**−0.427**	**−0.363**	**−0.358**	−0.063	0.016	0.058
	3rd	0.031	−0.080	**−0.214**	−0.093	0.132	0.083	0.067
FCMB	1st	−0.130	0.011	−0.199	−0.113	−0.112	−0.027	**−0.137**
	2nd	0.409	0.113	0.106	−0.069	−0.012	0.031	0.129
	3rd	0.243	0.274	−0.024	−0.025	0.002	0.090	0.115
	4th	−0.102	0.040	0.197	0.125	0.066	0.154	0.159
GTB	1st	−0.214	−0.225	−0.073	−0.045	−0.122	**−0.168**	**−0.184**
	2nd	0.273	0.094	−0.099	−0.034	0.023	−0.107	−0.053
	3rd	−0.160	**−0.500**	**−0.598**	**−0.339**	0.019	0.178	0.182
	4th	0.197	0.141	0.154	0.024	0.021	0.008	−0.093
Sterling	1st	**−0.516**	−0.206	−0.158	−0.080	0.058	0.077	0.126
	2nd	0.121	0.009	−0.001	−0.120	0.020	0.078	0.047
	3rd	0.389	0.103	−0.076	−0.008	0.001	0.044	0.124
	4th	−0.199	−0.245	−0.150	**−0.187**	0.020	0.071	0.113
United	1st	0.039	−0.102	0.185	**0.208**	0.077	0.000	−0.995
	2nd	0.262	0.011	−0.093	0.006	0.180	0.154	0.234
	3rd	0.178	0.206	0.197	0.118	0.047	0.058	0.012
Union	1st	0.225	−0.076	0.042	−0.170	**−0.170**	**−0.136**	**−0.089**
	2nd	0.294	0.441	0.444	0.272	0.148	0.052	0.067
	3rd	−0.176	−0.173	−0.141	−0.064	−0.105	−0.071	−0.015
Unity	1st	0.002	0.005	0.012	0.027	0.084	0.183	0.309
	2nd	0.336	0.369	0.155	−0.011	−0.081	−0.066	−0.018
	3rd	**−0.428**	**−0.264**	−0.153	−0.159	−0.048	0.001	0.077
Wema	1st	**−0.500**	**−0.503**	−0.178	−0.224	−0.131	**−0.140**	−0.154
	2nd	0.431	0.282	0.110	−0.013	−0.080	0.006	0.122
	3rd	0.007	0.021	0.034	0.058	0.124	0.224	0.374
	4th	0.422	0.476	0.271	0.212	0.284	0.314	0.217
	5th	−0.324	0.044	−0.090	−0.137	**−0.175**	−0.103	−0.032
Zenith	1st	0.339	0.168	0.239	0.102	0.110	0.087	−0.014
	2nd	0.411	0.500	0.075	0.034	−0.038	0.052	0.110
	3rd	−0.292	**−0.295**	**−0.301**	**−0.363**	**−0.210**	−0.127	−0.132
95% low	–	0.367	0.260	0.212	0.184	0.150	0.130	0.116
95% high	–	−0.367	−0.260	−0.212	−0.184	−0.150	−0.130	−0.116

For Wema, the selected values for m are 4, 5, 6, 7, 8 and 9 and 10.
In bold, evidence of mean reversion at the 5% level.

Table 11. Here we observe that most of the cases of mean reversion take place at the first subsamples, observing an increase in the degree of dependence as we move from one subsample to another. Thus, we can conclude by saying that the degree of dependence has increased across the sample period for most of the series examined.

4. Concluding remarks

This paper deals with the analysis of fractional integration and structural breaks in the daily share prices of banks in Nigeria, using data from 2001 to 2012. These data cover periods before and after the global financial crisis. Preliminary data description showed that from among the selected banks, First Bank had the highest average share price, while Unity Bank returned the lowest share price; the distribution of the banks share prices is positively skewed and leptokurtic except that of Union Bank. The analysis of fractional integration was carried out using both parametric and semiparametric methods. The results showed evidence of no mean reversion in most of the bank share prices since most of the orders of integration were equal to or higher than 1. The only exceptions were FCMB with uncorrelated errors and First Bank and GTB with autocorrelated disturbances. However, the absolute and squared return series displayed evidence of long memory ($d>0$) in the majority of the cases examined. This is consistent with what is observed in other more developed financial markets. Testing for the stability in the integration orders using structural breaks techniques, the results are heterogenous in terms of the number of breaks and the break dates, with all banks having at least two breaks over the sampled period. A common break is found in practically all cases at December 2008, a few month later after the global financial crisis. The heterogeneity in the number of breaks and in the break dates might be due to the fact that the banking system in Nigeria has undergone a number of reforms and consolidations between the years 2006 and 2012. Also, the global financial crisis has strongly affected the Nigerian banking industry.

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