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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)