Fixed Income Market Efficiency: Evidence from Kenya's 10-Year Local Currency Bond

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Abstract

This paper tests for long memory in the yield changes and volatility of Kenya's benchmark 10-year government bond, in order to evaluate the informational efficiency of the local currency market. Using the ARFIMA-FIGARCH model the statistical properties of yield changes and volatility are simultaneously estimated. Evidence of long memory in both yield changes and volatility are conclusively demonstrated. This finding suggests a pattern of time-dependence in the data, which stands against the efficient market hypothesis. In addition, the existence of long memory in the data is valid for all sample periods, suggesting that the recent bond markets reforms have not wholly produced the expected efficiency gains.

Keywords: *bonds, Long Memory, AFRIMA, ARFIMA-FIGARCH*

JEL Classification Code: *G1, G 12, G14.*

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I. INTRODUCTION

Long memory (or long-range dependence) in debt markets has important implications for the efficiency of the market in pricing fixed income securities. The efficient market hypothesis (EMH) provides the standard framework to analyse and interpret informational efficiency in capital market data. While a number of definitions of market efficiency are available, the random walk version of the EMH proposed by Bachelier (1900), formalised by Osborne (1959) and refined by Fama (1965, 1970) asserts that for a financial market to be efficient future prices, or returns, cannot be predicted from currently available information.

If yields in Kenya's 10-year benchmark bond display long memory, then they exhibit non-linear behaviour marked by distinct but non-periodic cyclical patterns; and, long-term dependence between distant observations. This, in turn, suggests that the fluctuations of the 10-year bond embody a predictable component; and hence, past trends in yield movements can be used to extrapolate future trends. In this light, long memory provides evidence against the weak-form version of the efficient market hypothesis.[2]

There are numerous studies that present evidence for and against long memory in financial markets. However, most of the research has concentrated on global equity markets (e.g., Poon, 2005 and references therein).In terms of the analysis of long memory dynamics in fixed income markets, the literature has mostly been limited to developed markets. For example, Bollerslev et al, (2000), McCarthy et al, (2004), Schotman et al, (2008) and McCarthy et al, (2009) all examined the various aspects of long memory in interest rates and yield spreads in order to determine its existence, magnitude and investment implications.

Research on long memory dynamics in fixed income markets in Africa is limited; notable exceptions include Thupayagale (2011), who demonstrates evidence of long memory in the volatility of South Africa's local currency 10-year bond using methods based on wavelets, and Thupayagale (2012),who analyses long memory behaviour among several emerging markets (including South Africa) and finds that the information content of long memory models does not generally lead to improved forecast accuracy relative to the standard GARCH process.

The purpose of this paper is to augment this line of analysis concerning the characterisation of long memory dynamics, by focusing on Kenya's local currency debt market given recent the implementation of structural reforms aimed at enhancing market efficiency and secondary trading activity. This study, therefore, contributes to the broader discussion concerning the state of capital market development in Africa by examining the efficiency of local bond markets with a view to evaluate the success of various policy initiatives designed to enhance the level of debt market operations.

This research extends the existing literature in the following ways. First, by determining if long memory exists in Kenya's bond market, since there does not appear to be any previous tests of long memory in this market. Second, long memory in bond yield changes and volatility are simultaneously estimated using the ARFIMA-FIGARCH model, which represent a relatively new innovation in time series analysis. Third, informational efficiency is examined in the market before and after reforms, in order to evaluate whether these reforms led to efficiency gains.

[2] The weak form of the EMH asserts that the current price incorporates all relevant historical information about bond yields. As such, changes in bond yields cannot, therefore, be predicted from past trends in yields.

To summarise key findings from the outset, evidence of long memory in Kenya's 10-year bond yield changes and volatility are recorded. Both parameters are statistically significant, suggesting that they represent an important characterisation of Kenya's bond market. Furthermore, this study finds evidence of long memory in both sample periods (i.e., the entire sample period and the post-reform sample period) indicating that Kenya's local currency bond market remains inefficient despite recent implementation of financial market reforms. However, the magnitude of the long memory parameters in the post reform period are smaller, suggesting perhaps, that some progress has been made, although further improvements are still required.

II. BOND MARKET REFORMS IN KENYA

Since the turn of the millennium, local currency emerging market debt has evolved from a niche market for credit specialists into a mainstream asset class, whereby emerging market debt is progressively becoming part of strategic holdings of global fixed income managers. However, it is important to observe that emerging markets are not homogeneous and these markets differ markedly in terms of the level of development. For instance, African bond markets (ABMs) are perceived by many investors as the terminus for investors searching for high yields. In addition, ABMs are, on average, less deep and liquid than their larger emerging market counterparts, owing to a variety of reasons, including: a narrow investor base; relatively small volumes of transactions; underdeveloped financial infrastructure; and bottlenecks in the trading, settlement and clearing infrastructure. Indeed, most ABMs - excluding South Africa - remain very small by world standards. Small size and associated low levels of liquidity, raise questions regarding the efficiency of these markets and the process of price determination. Using the EMH as a criterion, the theme of market efficiency is explored within the context of Kenya's bond market.

Promoting capital market development in Kenya has become an important component of the government's financial development strategy. In particular, recent reforms recognised the development of bond markets and the financing of capital formation as key factors bearing upon the prospects for long-term growth. The importance of the local bond market in Kenya, not only as a vehicle to fund the country's budget deficit, but also as a source for investments that are free of credit risk, that can serve as a benchmark for the development of the domestic corporate bond market and as an alternative to equity financing and bank lending has motivated policymakers to initiate measures designed to ameliorate conditions in the bond market.

In order to improve market efficiency in the domestic debt market, the Central Bank of Kenya, in collaboration with the Capital Markets Authority and the Nairobi Stock Exchange, initiated a program to enhance the efficiency and liquidity of the Kenyan government securities market as a key part of its strategy to develop the domestic bond market. Since September 2007, the Kenyan authorities have embarked on a focused issuance program aimed at building large and liquid benchmark bonds. This was achieved through larger issuance of new government bonds and re-openings of existing issues, therefore increasing the free-float available for secondary market purposes. By proactively helping to re-channel liquidity from off-the-run issues to benchmark bonds and then conducting more frequent auctions, the authorities have sought to increase the pool of assets available for secondary trading, thereby achieving critical sizes that are more easily tradable both by onshore and offshore investors. In addition, to more effectively conduct fiscal funding and align issuance more closely with budgetary requirements, the auction calendar and issuance schedule were further streamlined. These reforms brought operations and policies closer to internationally accepted principles and practices and have revitalised the government bond market by, among others, supporting larger and more frequent issuance and improved liquidity in the secondary market. Additional reforms included the introduction of the automated trading system (ATS) in December 2009. In fact, all government and corporate bonds are dematerialised and trade in an end-to-end automated platform, encompassing the placement of orders to matching and finally clearing and settlement. Furthermore, the Kenyan Government has committed itself to macroeconomic stability characterised by moderate inflation, trend growth and sustainable government deficits. Table 1 presents key macroeconomic indicators for Kenya. The growth and inflation outlook, along with a variety of key fiscal metrics, indicate improving conditions for Kenya's bond market to develop.

Table 1: Economic and Financial Indicators for Kenya

	2010	2011	2012	2013	2014F
Real GDP growth	5.8	4.4	4.6	4.8	5.9
CPI inflation	4.1	14.0	9.4	5.7	7.1
Current account/GDP	-7.9	-9.8	-10.4	-9.2	-10.6
FX reserves (USD, billions)	4.0	3.7	5.7	6.1	7.0
Months of import cover	3.9	4.2	4.3	4.1	4.2
Fiscal balance/GDP	7.2	-5.0	-5.6	-6.8	-8.7
Primary balance/GDP	-2.1	-1.9	-1.8	1.4	-1.6
General govt/debt	25.9	27.8	26.1	28.7	28.3
External debt/GDP	22.2	26.4	23.5	23.0	25.4
Policy rate	6.0	18.0	11.0	8.5	8.5
S&P Sovereign Rating	B+	B+	B+	B+	B+

Notes: 1. CPI inflation refers to the annual average inflation rate.
2. The government has an inflation target of 5% over the medium term.
3. The ratio of foreign exchange reserves to imports is expressed as months of import cover.
4. The policy rate refers to the year-end central bank rate.

Source: Reuters, Bloomberg, IMF, Central Bank of Kenya, Standard Chartered Research.

Table 2 presents an overview of debt markets in Kenya. In relation to treasury (or government) bonds, the fixed-rate 'plain vanilla' nature of the bond market is highlighted and common tenors are noted. Of particular interest are secondary market trading conditions where average daily turnover is estimated at between USD20-25 million. In terms of the taxation dispensation, a 15% withholding tax applies to listed bonds. The only exception relates to infrastructure bonds, which are tax exempt. This favourable tax treatment is motivated by the government's preference to further develop the level and quality of infrastructural development by encouraging investments in these bonds.

Table 2: Rates in Kenya

	T-bills	**T-bonds**	**Term auction deposit**
Issuer	Treasury		
Use of proceeds	Liquidity management/fiscal financing	Fiscal financing	Liquidity management
Curve span	91-to 364-day	2Y-30Y	7- to 28-day
Common tenors		2Y, 5Y, 7Y, 10Y, 15Y, 20Y	
Coupon		Fixed	
Coupon frequency		Semi-annual	
Day count		Actual/365	
Primary Market			
Auction style	Multiple-price	Multiple price	Multiple price
Average issue size	KES 2-5 billion	KES 18-20 billion	variable
Secondary market			
Average trade size	KES100 million	KES100 million	NA
Average daily turnover		KES1.7-2.2 billion	
Quotation convention	Yield	Yield	Yield
Settlement period	T+3	T+3	T+0
Bid/offer spread	15bps	50bps	NA

Note: 1. 15% withholding tax applies to listed bonds. The only exception relates to infrastructure bonds, which are tax exempt.
2. Secondary market fees comprise a 0.04% brokerage on consideration
3. All trades are required to go through a local broker

Source: Standard Chartered, Reuters, Bloomberg, Central Bank of Kenya and ABSA Capital Research

III. LONG MEMORY IN TIME SERIES

Models analysing long memory dynamics were first introduced by Hurst (1951). His investigation was motivated by hydrological considerations; in particular, the storage and distribution of water from Nile River given its non-periodic (flooding) cycles. Mandelbrot and Wallis (1968) described this feature as the 'Joseph effect' hinting to the biblical reference in which seven years of plenty were to be followed by seven years of famine. Long memory is associated with a correlation structure over long lags. Specifically, it describes a data series whereby observations in the remote past are highly correlated with observations in the distant future. Mandelbrot (1971) pioneered the application of long memory models to financial markets. His study triggered the examination of long memory dynamics across various securities and asset markets in order to analyse and interpret financial market data.

To define a long memory model formally, let υ_τ be the autocovariance function with a time lag τ of a stationary process X_t, there exists long memory in X_t if its autocovariance function $\rho(\tau)$ decays monotonically and hyperbolically to zero. This asymptotic property can be stated as:

$$\rho_\tau \approx |\tau|^{2d-1} \text{as} |\tau| \rightarrow \infty \quad (1)$$

Where $d \in (0, 0.5)$ is the long memory parameter. In the case where d> 0.5, the series is nonstationary. Meanwhile, for $d \in (0, 0.5)$, the series is described as antipersistent, which is a measure of the decline in statistical significance between distant observations.

A variety of measures have been used to detect long memory in financial time series. The most widely used in contemporary econometric analysis are the fractionally-integrated I(*d*) time series models introduced by Granger and Joyeux (1980) and Hosking (1981). Fractionally integrated processes are distinct from both stationary and unit-root processes in that they are persistent, but are also mean reverting; and, therefore provide a flexible alternative to standard I(1) and I(0) processes.

To estimate the long memory parameter, *d*, in financial time series data, the most familiar model is the autoregressive fractionally integrated moving average (ARFIMA (*p, d, q*)) model, which captures temporal dependencies in the conditional mean process. Subsequent to this, Baillie *et al*., (1996) developed the fractionally integrated generalised autoregressive conditional heteroskedasticity (FIGARCH (*p, d, q*))model, which captures long memory in the conditional variance of a time series. Since non-zero values of the fractional differencing parameter imply dependence between distant observations, substantial attention has been directed to the analysis of fractional dynamics to test empirical and theoretical propositions in financial economics. Against this background, a recent innovation has been the joint estimation of long memory in returns and volatility using the ARFIMA-FIGARCH model, which is the subject of the next section.

IV. EMPIRICAL METHODOLOGY

Modelling Returns: ARFIMA Model

The general specification for the ARFIMA (*m, d, n*) class of models can be expressed as:

$$\phi(L)\,(1 - L)^d y_t = \theta(L)\,\varepsilon_t \quad (2)$$

Where L is a lag operator, $\phi(L)$ and $\theta(L)$ are polynomials in the lag operator of orders m and n respectively. Further, $\phi(L) = 1 - \sum_{j=1}^{m} \phi_j L^j$ and $\theta(L) = 1 + \sum_{j=1}^{n} \theta_j L^j$. All the roots of $\phi(L)$ and $\theta(L)$ lie outside the unit circle. The residual, ε_t, follows a white noise process with variance, σ^2. The fixed income yield (change) at time, t, denoted y_t and $d$is to the fractional differencing parameter. The long memory property arises when fractional differencing parameter, $d \in (0, 0.5)$.

Modelling Volatility: FIGARCH Model

The FIGARCH process can be derived from the standard GARCH (p, q) model, which can be expressed as:

$$h_t = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)h_t \quad (3)$$

Where h_t and ε_t^2 are conditional and unconditional variances of ε_t respectively, $\omega = \varepsilon^2[1 - \beta(1) - \alpha(1)]$, and $\phi(L) = 1 - \sum_{j=1}^{q} \phi_j L^j$ and $\beta(L) = 1 + \sum_{j=1}^{p} \beta_j L^j$. The GARCH ($p, q$) process in Equation (3) can be rewritten as an ARMA (m, p) process in ε_t^2,

$$[1 - \alpha(L) - \beta(L)]\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t \quad (4)$$

where $v_t \equiv \varepsilon_t^2 - h_t^2$ has a zero mean and is serially uncorrelated, i.e., $E_{t-1}(v_t) = 0$. To ensure covariance stationarity, the roots $[1 - \alpha(L) - \beta(L)]$ and $[1 - \beta(L)]$ are constrained to lie outside the unit circle. When the autoregressive lag polynomial, $1 - \alpha(L) - \beta(L)$, contains a unit root, the GARCH (p,q) process is said to be integrated in variance and the process is called an integrated GARCH (or IGARCH) process (Engle and Bollerslev, 1986) and is given by:

$$\phi(L)(1 - L)\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t \quad (5)$$

From this model, the general specification of the FIGARCH model can be obtained by introducing the fractional differencing operator, $(1 - L)^{\bar{d}}$, as such:

$$\phi(L)(1 - L)^{\bar{d}}\,\varepsilon_t^2 = \omega + [1 - \beta(L)]v_t \quad (6)$$

The FIGARCH (p, d, q) model encompasses other GARCH based models, and is equivalent to the GARCH process when $\bar{d} = 0$ and to the IGARCH when $\bar{d} = 1$ (see Baillie*et al,* 1996). The FIGARCH$\left(1, \bar{d}, 1\right)$model will be estimated by maximum likelihood methods, which are both consistent and asymptotically efficient. In particular, the following log-likelihood is maximised:

$$\eta = T\left\{ln\Gamma\left[0.5(df + 1)\right] - ln\Gamma(0.5df) - 0.5ln\left[\pi(df - 2)\right]\right\}$$

$$- 0.5\sum_{t=1}^{T}\left\{ln(h_t) + (1 + df)ln\left[1 + \varepsilon_t^2/(h_t[df - 2])\right]\right\} \quad (7)$$

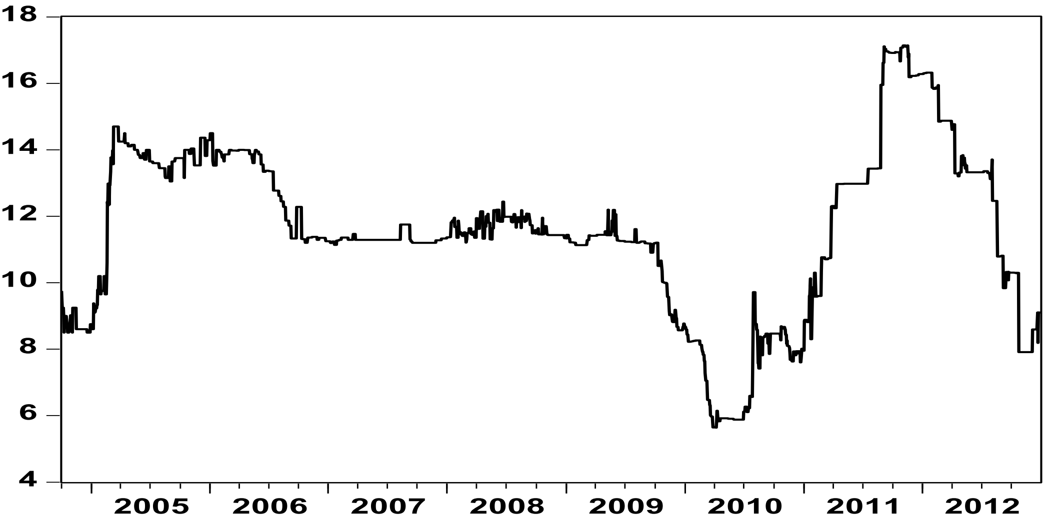
Where df denotes the degrees of freedom. Following the results of previous findings that returns are not normally distributed, estimation is based on the student t distribution.

V. EMPIRICAL ANALYSIS

This analysis is based on daily yields on Kenya's benchmark 10-year local currency bond. The data, which are obtained from Thompson Reuters, span the period from October 1, 2004 to December 31, 2012.Figure 1 plots the evolution of the 10-year yield over the sample period. The 10-year yield peaked at 17.2 percent in 2011 from a trough of 5.6 percent in 2010. The Central Bank of Kenya increased its key lending rate by 1225 basis points to 18 percent during

2011 as a sharp currency depreciation and a severe drought took headline inflation to 19 percent year-on-year. The yield on the 10-year bond rose in tandem with these developments.

Figure 1. Daily Yields of Kenya's 10-YearLocal Currency Bond



(a) Preliminary Observations

Before embarking on further statistical analysis, the yield on Kenya's 10-year yield was checked for stationarity and it was determined that the yield becomes stationary after being differenced once (as reflected in the unit root tests). Hence, all subsequent empirical analysis is conducted on yield changes (differences). At the same time, LM and normality tests highlight the existence of non-normality and ARCH effects in the data. Table 3 presents the summary statistics on the yield difference in Kenya's 10-year bond.

Table 3. Description of the Data

No. of observations	2151	
Mean	-0.0003	
Standard Deviation	0.1944	
Skewness	0.6699	
Kurtosis	52.4949	
Normality test	Chi^(2)=219719	
ARCH (5) test	F(5, 2141)=82.8436	
ARCH (10) test	F(10, 2131)=43.9522	
Unit root test		
	Constant	Constant and Trend
ADF	-48.5737**	-48.5804**
PP	-48.6143**	-48.6272**

(b) Results from GARCH Models

The non-white noise characteristics of changes in Kenya's benchmark 10-year Treasury note motivate an extension of the model in order to take them into account in the statistical model to be estimated. To this end, the GARCH (1, 1) model is estimated using the assumption of the

Student *t* distribution.[3]This model allows for the modelling of volatility persistence based on some stylised facts usually observed in high-frequency financial time series data, among them, the presence of thick tails, time-varying correlations and volatility clustering. Table 4presents the models and highlights the importance of GARCH effects by showing that the GARCH and ARCH terms are statistically significant over both sample periods.

Evidence of persistence in variance as measured by the GARCH model is reflected in the magnitude and significance of the ARCH and GARCH terms (indeed, as this sum approaches unity the greater the degree of persistence). If the sum of GARCH and ARCH terms are equal to unity (i.e., $\alpha+\beta=1$), then any shock to volatility is permanent and the unconditional variance is infinite. In this case, the process is called an IGARCH (as shown in equation 5). Therefore, in order to have an indication of long memory in the 10-year note persistence in variance is measured. Volatility persistence over the two sample periods differs (i.e., the entire sample period and the post reform period) are 0.8994 and 0.8337, respectively. In other words, over both sample periods the level of Kenya volatility is persistent, which indicates evidence of long memory in the volatility structure. It is also observed that the level of volatility persistence is lower in the post-reform period relative to the full sample period. This difference may signal *prima facie* evidence of the impact of reforms. Diagnostic tests to assess the adequacy of the model are performed by applying the Ljung-Box Q statistic test to standardised and squared standardised residuals. These diagnostics suggest that the estimated models are appropriate for the data considered. Specifically, the Ljung-Box test determines whether a time series consists of random variables; a large p-value (i.e., p-value› 0.05) suggests evidence of no dependence in the residuals. This, in turn, indicates that the model is correctly specified. Furthermore, the various sign bias tests suggest that there are no volatility asymmetries in the data that need be incorporated into the model.

Table 4. GARCH Estimates

	3/6/2004 - 31/12/2012	1/9/2009 – 31/12/2012
Constant	-0.4961 [0.4393]	-0.0887 [0.7845]
ω	0.0051 [0.0291]	8.3002 [7.9149]
α	0.6968 [0.0508]**	0.6811 [0.0376]**
β	0.2026 [0.0027]**	0.1526 [0.0138]**
df	2.0000 [0.0001]**	2.3001 [0.0292]**
Q(5) 1/	2.1427	5.7188
Q(5) 2/	2.6235	6.2580
Sign bias test	1.4017	3.5538
Negative size bias test	1.7790	0.7446
Positive size bias test	3.8367	2.2253
Joint test	8.1031**	2.8839

Note: 1. The Ljung-Box Q test applied to standardised residuals
2. The Ljung-Box Q test applied to squared standardised residuals
The numbers in () and [] refer to lag lengths and standard deviations
(**) and (*) indicates statistical significance at the 1% and 5% levels, respectively.

[3] To select the lag length in the GARCH(p,q) model and other subsequent models used in the study the Schwarz Bayesian information criterion (SBIC) is employed. The SBIC is preferred to other standard information criteria (i.e., the Akaike and Hannan-Quinn information criteria) given its statistical properties; in particular, the SBIC will asymptotically deliver the correct model order.

(c) Results from ARFIMA-FIGARCH Models

A disadvantage of the standard GARCH model is its inability to capture long memory in the data. Therefore, this study now turns to the estimation of the fractional differencing parameter in Kenya's bond market using the ARFIMA-FIGARCH model, which is the main interest of this paper. To model persistence in changes in the benchmark 10-year yield and its volatility simultaneously maximum likelihood methods are used to estimate the ARFIMA-FIGARCH model. The ARFIMA part of the equation provides a basis to test for market efficiency by examining the size of the fractional differencing term, d, in the mean equation. In particular, d measures the adjustment speed (relative to a stationary ARIMA case where $d = 0$) and, hence, permits conclusions based on the EMH as a criterion. On the other hand, the FIGARCH part of the model captures long memory in the conditional variance of the data; and hence, provides insights into the behaviour of volatility in the 10-year bond. Table 5 presents estimates of the ARFIMA-FIGARCH model; in particular, the size, sign and significance of d and $\bar{d}$, are of interest as they capture long memory in changes in the yield and its associated volatility, respectively. Furthermore, over both the full sample and the post-reform sample the ARFIMA-FIGARCH and ARFIMA-FIGARCHmodels are employed, respectively.[4] The long memory parameters, d and $\bar{d}$ are presented in Table 5. In addition, the models highlighted in Table 5 appear to be well specified, since there appears to be no evidence of autocorrelation in the residuals or volatility asymmetries in the data that need to be accounted for.

Table 5. ARFIMA-FIGARCH Estimates

	3/6/2004 - 31/12/2012	1/9/2009 – 31/12/2012
Constant	0.2634 [0.2116]	0.3346 [0.2951]
d	0.3603 [0.0992]**	0.2846 [0.1307]*
ω	1.1132 [0.0731]**	0.0965 [0.0271]**
$\bar{d}$	0.1519 [0.0287]**	0.1468 [0.0624]**
β	0.6645 [0.2558]	0.4474 [0.0085]**
Ø	0.3170 [0.0122]	0.3082 [0.0643]
df	2.6311 [1.7130]	4.4230 [1.3026]*
Q(5) 1/	1.7656	0.1192
Q(5) 2/	2.1175	2.2305
Sign bias test	0.1325	4.6269
Negative size bias test	1.0443	2.1919
Positive size bias test	1.7413	2.4313
Joint test	8.3137	6.1117

Note: 1. The Ljung-Box Q test applied to standardised residuals
2. The Ljung-Box Q test applied to squared standardised residuals
The numbers in () and [] refer to lag lengths and standard deviations
(**) and (*) indicates statistical significance at the 1% and 5% levels, respectively.

ARFIMA MODEL

Market efficiency is considered by examining the size of the fractional differencing term, d, in the mean equation. Over the full sample period, the long memory parameter for Kenya's 10-year benchmark bond is 0.3603 and is statistically significant. This implies that changes in the 10-year bond yield are autocorrelated and, hence, future changes in the 10-year yield can be predicted using past yield data. This result suggests that weak-form efficiency does not hold; since a predictable component to the data is revealed. For the post-reform period,

[4] Lag lengths are computed on the basis of the Schwarz Bayesian information criterion.

the long memory parameter is 0.2846, indicating that the intensity of predictability in the data generating process is reduced, relative to the full sample period. In addition, the effect is only significant at the 5 percent level of significance. These results, therefore, indicate the existence of long memory effects in both sample periods. However, the strength is smaller and less statistically significant in the post-reform period. Nonetheless, the results highlight the importance of modelling long-range dependence in bond yield data and points to market inefficiency in both sample periods. Given that in both periods the fractional differencing term is statistically different from zero.

FIGARCH MODEL

Evidence of long memory in the volatility of changes in Kenya's 10-year bond yields is found in the full sample and post-reform sample period. Findings from this model are shown by $\bar{d}$ in Table 5. The fractional differencing term, $\bar{d} = 0.1519$, over the full sample period is significantly different from zero. This indicates a pattern of time dependence in the volatility of changes in yields that may allow for past information to be used to improve the predictability of future volatility. Meanwhile, over the post-reform period, $\bar{d} = 0.1468$, and is also statistically significant. These findings indicate the importance of long-range dependence in the volatility structure of Kenya's Treasury note. This finding furthermore indicates that future volatility is a function of its past value and so is predictable from past information. The significant size of the fractional differencing parameters in this study underscores the importance of modeling long memory dynamics in Kenya's 10-year bond.

VI. CONCLUSION

The informational efficiency of Kenya's local currency bond market has been studied by examining the time series properties of the benchmark 10-year bond from June 3, 2004 to December 31, 2012. This study differs from previous research in a number of respects. First, it focuses on the long memory attributes of Kenya's local currency market, which appear not to have been conducted so far. Second, it evaluates market efficiency over the entire sample and after the implementation of key reforms in Kenya's capital markets in order to gauge their success. Third, estimation is conducted using time series techniques that allow for the simultaneous modeling of persistence in changes in yields and their volatility.

In sum, the results of the ARFIMA-FIGARCH model suggest that changes in Kenya 10-year bond yields are characterised by stochastic processes which have a predictable component. This, in turn, implies a departure from the EMH, suggesting that relevant market information was only partially or gradually reflected in bond yield changes.

Furthermore, this paper presents evidence of long memory in bond yield changes and their corresponding volatility regardless of the sample period. In relation to the post-reform sample, the long memory estimates are quantitatively smaller, perhaps suggesting some progress towards improvement with respect to informational efficiency. However, the fact that the fractional differencing term is statistically different from zero in both periods indicates that the market is still informationally inefficient – albeit at lower levels. This paper points to a number of possible factors behind the absence of improvements in market efficiency, despite the recent reforms in the bond market.

A prerequisite for bond market liquidity is a framework that balances the demand and supply side factors. However, the Kenyan market remains characterised by a severe structural shortage of bonds, with demand from annuity providers far exceeding available supply, hence the lack of liquidity. Another feature in Kenya pertains to the presence of non-synchronous trading or non-trading-effects which, in turn, reflect the small market size and further compound illiquidity and hinder market efficiency, despite the progress made to date in terms of capital market development. On the other hand, it is also anticipated that the implementation of primary dealer rules will enhance the price discovery process and connect the buyers and sellers more easily.

Finally, while this analysis is focused on Kenya's local currency 10-year bond, further analysis could usefully be conducted in a number of directions. One extension would be to investigate the exact causes of the inefficiencies in the Kenyan bond market. Another possibility would be to expand country coverage and compare our findings with those in other local-currency markets.

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