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The impact of inflation rate on stock market returns: evidence from Kenya

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Abstract This study examined the stochastic properties of inflation rate, stock market returns and their cointegrating residuals using monthly data for the period 1993 to 2015. The Autoregressive Fractionally Integrated Moving Average (ARFIMA)-based exact maximum likelihood estimation was employed to determine the integration orders of the individual variables as well as the cointegrating residuals. Results from the ARFIMA model indicate that the month-on-month inflation rate, year-on-year inflation rate and stock market returns have non-integer orders of integration. This is inconsistent with the stationary/nonstationary results often obtained from the conventional unit root tests and implies that any shocks to the variables are highly persistent but eventually disappear. The results also reveal that the cointegrating residuals have non-integer orders of integration, suggesting that deviations from the long run equilibrium are prolonged, contrary to the assumption held under the conventional cointegration framework. The Fractionally Integrated Error Correction Model (FIECM) reveals that the year-on-year inflation rate positively granger causes stock market returns. This supports Fisher Effect and implies that stock market returns in Kenya provide shelter against inflationary pressures. This is the first study to empirically examine fractional cointegration and ARFIMA-based Granger Causality between inflation rate and stock market returns in Kenya.

Keywords Stock returns · Inflation rate · ARFIMA models

JEL Classifications C13 · E44 · G12

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1 Introduction

Stock market returns provide useful signals regarding the future state of the economy, including the economic and financial status (Hamrita and Trifi 2011). Specifically, stock market returns drive the allocation of resources across sectors of the economy. Their stochastic behaviour also provides information concerning market expectations and risk attitudes of investors. Additionally, even though macroeconomists, financial economists and actors in the financial market use stock market indices to understand trends in the economy, describe stock markets and compare returns on specific investments (Hautcoeur 2011), stock market returns are more preferable because they provide traders and investors with a scale-free summary of the ever rapid inflow of information into the stock market (Lo et al. 1997).

Equally, given their more attractive statistical properties (Lo et al. 1997), stock market returns are useful to policymakers, researchers and stock market participants keen on making various forecasts, developing regulatory rules, constructing portfolio strategies or determining implications for policy. On the whole, understanding the trends of stock market returns is critical to evaluating the events in the financial market, monitoring the evolution of the economy, and situating the economy within the international arena.

Consequently, developed and developing countries are investing heavily in improving their stock markets as avenues for mobilizing and pooling domestic savings and efficiently allocating the funds to projects with best returns to the owners of the funds (Yartey and Adjasi 2007**.** In Africa, stock markets that have played key roles in the growth of the respective domestic economies include the Johannesburg Stock Exchange (JSE) of South Africa, Egyptian Stock Exchange, Mauritius Stock Exchange, Bourse de Casablanca of Morocco, Nigeria Stock Exchange (NSE), Botswanan Stock Exchange (BSE), and the Nairobi Securities Exchange (NSE) (PwCIL 2017).

Since its inception in 1954, the Nairobi Securities Exchange (NSE) has gone through several reforms with a view to improving capacity and enhancing the Exchange's efficiency. Among the most recent reforms include the commencement of the trading of Exchange Traded Fund (ETF) and the introduction of tax neutrality measures aimed at creating an enabling environment within the NSE for the Real Estate Investment Trusts (REITs) and Asset Backed Securities (ABS) (CMA 2017). These measures are expected to contribute to the acceleration of the country's economic growth and prosperity (NSE 2010).

The NSE particularly provides a platform where borrowers access long term investment funds from lenders at low cost (NSE 2010). It is this platform that enables corporations, the government and individuals to raise money to expand business activities, create employment and contribute to the general growth of the overall economy. For instance, investment capital worth 117 million USD was raised from the NSE in 2016 (PwCIL 2017). Likewise, courtesy of the NSE, investors often use money managers to plan their shares and bonds to enable them solve common problems such as payment of school fees, medical costs or retirement expenses (NSE 2010).

Furthermore, the NSE is Africa's fourth largest stock exchange in terms of trading volumes, and the fifth in terms of market capitalization as a percentage of GDP (NSE 2010).The NSE (which accounts for 90% of stock market activities in the East African region) also serves as an ideal frontier market for foreign investors keen on getting exposure to the East African region because many firms listed at the NSE operate beyond Kenya's borders (NSE 2010). However, before deciding to commit their funds in a stock market, investors often consider various factors among them the stochastic behaviour of stock market returns as well as factors that influence the behaviour of the stock market returns (Chen et al. 1986).

Stock market returns are systematically influenced by various types of information which arrives randomly to the stock market. A key type of such influential information is news regarding the evolution of inflation rate (Demirhan 2016; Gupta and Modise 2013). Inflation is a major concern to investors because they expect to be compensated in terms of higher stock market returns to maintain their real returns (Fisher Effect, Fisher 1930). The Fisher Effect (FE), in its strict interpretation, suggests that if the stock market is efficient, then investors expect nominal stock market returns to move on a one-to-one basis with expected inflation rate. However, since expected inflation rate is not observable, actual inflation rate is often a reasonable proxy, based on the theory of rational expectations (Rushdi et al. 2012).

On the other hand, inflation poses a serious threat to long-term investors since it erodes the returns of financial assets, including stock market returns, by undermining economic growth (Fama 1981). This can in turn result into a rise in prevailing interest rates and depress the performance of the overall economy. Furthermore, stock market returns often reflect valuation of cash flows over long horizons in the future (Alagidede and Panagotidis 2010). Consequently, monthly stock market returns are likely to have stronger relationships with changes in inflation rate projected many months into the future (i.e. year-on-year inflation rate) rather than with changes in current month's inflation rate (i.e. month-on-month inflation rate).

The importance of a clear understanding of the stochastic properties of stock market returns, month-on-month inflation rate, year-on-year inflation rate and the respective cointegrating residuals can therefore not be over-emphasized. However, debate on the stochastic properties of these individual variables is far from being settled. For instance, vast studies employ standard unit root tests and either conclude that stock market returns are stationary (Ouma and Muriu 2014) or nonstationary (Erita 2014; Kimani and Mutuku 2013) in level form. Equally, other studies establish that inflation rate and stock market returns are stationary in level form (Ouma and Muriu 2014) while others report nonstationarity of inflation rate and stock market returns (Kimani and Mutuku 2013) in level form. In contrast, Anoruo and Gil-Alana (2011) demonstrate that stock market returns possess nonstationary long memory.

Additionally, most studies presume that inflation rate and stock market returns are cointegrated in the conventional form such that their cointegrating residual is I(0), making deviations from long run equilibrium to dissipate rapidly (Erita 2014; Frimpong 2011; Gohar et al. 2014; Jawaid and Anwar 2012).

Majority of the existing univariate analyses also focus on the conventional I(1) case where persistence in time series is exponentially reduced from 1 to zero (Cakan and Ejara 2013; Erita 2014; Kimani and Mutuku 2013). However, the individual macroeconomic variables are likely to evolve over time through non-integer orders of integration (Teyssiere and Kirman 2007).

Studies that report that the individual macroeconomic variables are nonstationary in levels suggest that shocks to the respective variables persist indefinitely and might become explosive if active policy measures are not taken. In contrast, those that report presence of a fractional integration suggest that the individual variables may be highly persistent but shocks to them eventually disappear, allowing the variables to return to their pre-shock mean values. The traditional stationary/nonstationary [i.e. I (0)/I (1)] dichotomy is therefore too restrictive since an individual variable can be non-stationary without necessarily being a unit root process (Caporin et al. 2013).

Long memory processes are usually analyzed by Autoregressive Fractionally Integrated Moving Average (ARFIMA) models introduced by Granger and Joyeux (1980) and Hosking (1981). A stationary time series *Yt* is said to follow an *ARFIMA*(p, d, q) process if:

$$\Phi(\mathrm{L})(1-\mathrm{L})^{\mathrm{d}}\mathrm{Yt} = \theta(\mathrm{L})\varepsilon\mathrm{t} \tag{1}$$

where $\Phi(L)$ and $\theta(L)$ are autoregressive and moving average polynomials such that $\Phi(L) = 1-\phi 1L-\ldots\ldots\ldots\ldots\ldots\phi pL^p$ and $\theta(L) = 1-\psi 1L-\ldots\ldots\ldots\ldots\ldots\ldots-\psi qL^q$, L is the lag, d is the fractional differencing parameter while εt is white noise error term.

Just as the conventional modeling of univariate time series can be extended to fractional modeling by avoiding the restrictive I(0)/I(1) assumption, conventional cointegration can also be generalized into fractional cointegration where the residual series are allowed to take on real values in the range of [0, 1]. Such a situation results into the relationship between variables responding to exogenous shocks but at the same time exhibiting some short run persistence (Cheung and Lai 1993). Therefore, in the ARFIMA framework, the differencing parameter d is allowed to take on real values rather than being limited to the integer field.

Unlike in the developed stock markets such as the US, the presence of long memory in emerging stock markets has received little attention. This study therefore assumed that stock market returns from the NSE and inflation rate in Kenya were fractionally integrated and that the cointegrating residuals between the two variables were also long memory processes. The study therefore sought to examine the relationship between inflation rate and stock market returns within the context of an ARFIMA framework using data from Kenya over the period 1st January 1993 to 31st December 2015.

Consistent with the research problem, this study sought to address the following research questions: First, to what extent do stock market returns in Kenya evolve over time through non-integer orders of integration? Second, to what extent does inflation rate in Kenya exhibit long memory characteristics? Finally, to what degree does the cointegrating residual between inflation rate and stock market returns in Kenya display long memory properties?

The results suggest that the month-on-month inflation rate, the year-on-year inflation rate and stock market returns have non-integer orders of integration. The results also indicate that the cointegrating residuals have a non-integer order of integration. Additionally, the results show that the year-to-year inflation rate positively granger caused stock market returns.

The rest of the paper is organized as follows. Section 2 provides a brief literature review while section 3 outlines the adopted research methodology. Section 4 discusses the data and sources. The empirical results and their discussion are presented in section 5 while section 6 concludes.

2 Literature review

Theories which tend to describe how inflation rate is related to stock market returns can be categorized into two. One set argues that inflation rate is positively and causally related to stock market returns (Fisher Effect, Fisher 1930) while the other asserts that the relationship between the variables is negative and not causal (Proxy Effect, Fama 1981).

Fisher (1930) argued that expected rate of return of a financial asset (reflected by the nominal interest rate) should consist of expected real rate of interest and expected rate of inflation. According to this theory, expected real rate of interest is constant (only depends on the rate of return on capital) while the nominal rate of interest reflects all available information on the future levels of inflation rate. Consequently, the theory asserts that a permanent change in inflation rate should cause an equal change in the nominal interest rate. This suggests that nominal interest rate should respond positively on a one-for-one basis to a change in expected inflation rate. Generalized to real assets, the theory suggests that common stock returns should consist of real stock returns and expected inflation rate. With the real stock returns being constant, an increase in expected inflation rate should lead to a one-for-one increase in common stock returns. This strict interpretation of the Fisher Effect suggests that stocks should provide an efficient hedge against rising inflation rates. Hence, if the theory holds, returns from stocks should compensate investors for increases in expected as well as in unexpected inflation rate.

On the contrary, the Proxy Effect (Fama 1981) asserts that a negative correlation, which is not causal, exists between stock market returns and inflation rate. The theory argues that this negative correlation is as a result of a positive correlation between stock market returns and real economic activity coupled with the negative correlation between inflation rate and real economic activity. According to the theory, rising inflation rate is expected to depress real economic activity and in turn negatively affect future corporate cash flows.

Debate on the previous results on the stationarity of inflation rate, stock market returns and their cointegrating relationship also remains unsettled. This is because whereas some of the studies found that inflation rate and stock market returns are nonstationary in levels (Alagidede and Panagotidis 2010; Kimani and Mutuku 2013), implying that the variables do not revert to their long run mean values following a shock, others concluded that both variables are stationary in level form (Ouma and Muriu 2014). Additionally, some authors concluded that stock market returns are stationary whereas inflation rate is nonstationary in level form (Kirui et al. 2014).

Other studies however challenge the application of the restrictive I (0)/I (1) analysis to the individual time series and instead employ their fractional integration counterparts. For instance, Anoruo and Gil-Alana (2011) applied the Whittle function in the frequency domain and Robinson (1994) test to data from ten African countries (Kenya, Morocco, Tunisia, Nigeria, Egypt, Zimbabwe, Mauritius, Botswana, Namibia, and South Africa) and found that the differencing parameter (d) of stock market returns was greater than 1. A similar result was established by Balparda et al. (2015) using data from Kenya for the period 2001 to 2009 and Robinson (1994) test. This suggests that stock market returns in Kenya possess long memory but are not mean reverting.

Likewise, Aye et al. (2012) used daily data from Brazil, Russia, India, China, and South Africa (BRICS) over the period 1995:09–2012:07 to examine existence of long memory in stock market returns. The authors employed Whittle estimator (WHI), the Geweke and Porter-Hudak estimator (henceforth referred to as GPH), Rescaled range estimator (RR) and Approximate Maximum Likelihood estimator (AML) and demonstrated that the differencing parameter of stock market returns was greater than 0.5 for Russia, India and China. This implies that the variable had nonstationary long memory but was mean reverting. This further means that shocks to the variable remained persistent but eventually dissipated, letting the variable to return to its long run equilibrium level.

Similarly, disagreements exist between studies that focused on long run relationship between inflation rate and stock market returns. In particular, Kim and Ryoo (2011) employed a two-regime threshold vector error-correction model (TVECM) and monthly data from the US between 1900 and 2009. They found that stock market returns moved on a one-to-one basis with inflation rate in the long run, thus supporting the predictions of FE (Fisher 1930). However, Kimani and Mutuku (2013) disputed the existence of FE when they applied Johansen-Juselius VAR-based cointegration test on data from Kenya during the period 1998:12–2010:06. On the other hand, Pal and Mittal (2011), using Johansen's co-integration test, error correction mechanism (ECM) and data over the period 1995:01–2008:12, confirmed that a long run relationship existed between inflation rate and stock market returns in India. This suggests that the two variables moved closely together in the long run. However, the authors did not support existence of Fisher Effect since inflation rate was negatively related to stock market returns.

There is also no concurrence on the existence of Granger causality between inflation rate and stock market returns (Ada and Osahon 2015; Dasgupta 2012; Frimpong 2011; Issahaku and Ustarz 2013). For example, Ada and Osahon (2015) using vector error correction model (VECM) and annual data during the period 1980–2011, found that causality ran from stock market returns to inflation rate in Nigeria, providing evidence in support of the Reverse Causality Hypothesis (RCH) (Geske and Roll 1983). This means that knowledge of past values of stock market returns could help improve forecasts of inflation rate while the converse is not true. In direct contrast, Dasgupta (2012), using ECM and monthly data from 2007:04–2012:03, failed to establish either unidirectional or bi-directional causality between inflation rate and stock market returns in India. This suggests that the variables are driven by different factors in the long run.

Other studies however found that a unidirectional causality originated from inflation rate to stock market returns. For instance, Frimpong (2011) used monthly data during the period 1990:11–2007:12 to determine the direction of causality between Databank Stock Price Index returns, 3-month T-Bills rate, cedi/dollar exchange rate and a change in CPI as a proxy of inflation rate in Ghana. The author adopted standard Granger causality test and established that a unidirectional causality ran from inflation rate to stock market returns. Likewise, Issahaku and Ustarz 2013 employed an ECM and monthly data over the period 1995:01–2010:12 and established that a unidirectional positive long run causality originated from inflation to stock returns in Ghana.

However, a weakness in all these studies is that they seem to assume that the error correction term has to adjust towards equilibrium as envisaged under the conventional cointegration framework whereas the equilibrium error term itself might follow a fractionally integrated process (Caporin et al. 2013; Okunev and Wilson 1997). For instance, Caporin et al. (2013), using fractional vector error correction model (FVECM) and data over the period 2003–2010 established that the difference between the daily highs and lows of the Dow Jones Industrial Average (DJIA) index were fractionally cointegrated. This implies that the high and the low prices may temporarily diverge but eventually converge in the long run. This further suggests that investors with path-dependent trading strategies can capitalize on the predictability of the daily high prices to earn above average returns with no input of funds.

Likewise, using a nonlinear fractional cointegration model, Okunev and Wilson (1997) established that the real estate market and the stock market in the US were fractionally cointegrated implying that movement of the real estate towards the stock market was very slow such that divergence between the two markets was prolonged. The authors however failed to find cointegration between the two markets using (conventional) linear cointegration techniques. This is proof that fractional cointegration is superior in the sense that they incorporate nonlinear data generating processes. This further implies that the cointegrating residual does not need to be exactly I(0) for it to be mean-reverting.

This was given credence by Kiran (2011) who applied fractional cointegration framework to monthly data from 1990 to 2009 and established that inflation rate (proxied by oil prices) and stock market returns were fractionally cointegrated for Germany, UK, US and Canada. This suggests a much slower adjustment process and higher overall costs of deviations from equilibrium than would be obtained through conventional cointegration and Granger causality frameworks. The result further suggests that policy intervention may be required to drive back the two variables to their long run equilibrium should they be driven apart by either political or economic shocks.

In summary therefore, despite the result indicating that stock market returns in Kenya possess long memory (Anoruo and Gil-Alana 2011; Balparda et al. 2015), no study seems to have been designed to examine the possible existence of a fractional cointegration between stock market returns and inflation rate in Kenya.

3 Empirical models

3.1 Univariate ARFIMA models: Fractional integration

This study employed an ARFIMA model to empirically determine the integration orders of the two measures of inflation rate and stock market returns following Aye et al. (2012). However, unlike Aye et al. (2012) who used the GPH nonparametric estimator, this study employed the parametric Exact Maximum Likelihood (EML) estimator (Sowel 1992) which has the capability to simultaneously estimate the short memory as well as the long memory parameters of the variables of interest. The study therefore estimated the following univariate ARFIMA models:

$$(1-L)^{d1} NRt \tag{2}$$

$$(1-L)^{d2} MOMt \tag{3}$$

$$(1-L)^{d3} YOYt \tag{4}$$

Where $(1-L)^{d1}$ is the fractional differencing operator for stock market returns with $d1$ being the fractional differencing parameter for stock market returns. NRt represents the stock market returns, $MOMt$ is the month-on-month inflation rate, and $YOYt$ is the year-on-year inflation rate.

This study used both measures of inflation rate (month-on-month inflation rate and year-on-year inflation rate) because stock market returns often reflect valuation of cash flows over long horizons in the future (Alagidede and Panagotidis 2010). Consequently, monthly stock market returns are likely to have stronger relationships with changes in inflation rate projected many months into the future (i.e. year-on-year inflation rate) rather than with changes in current month's inflation rate (i.e. month-on-month inflation rate).

3.2 Bivariate ARFIMA models: Fractional cointegration

This study hypothesized that both measures of inflation rate and stock market returns were each fractionally integrated. This implies that their cointegrating residuals might also have been fractionally integrated (Caporin et al. 2013). To test this, the study fitted ARFIMA models to each of the cointegrating residuals derived from regressing stock market returns on each of the measures of inflation rate (Cheung and Lai 1993; Caporin et al. 2013). It used the following models:

$$(1-L)^{d4}Rnrmomt \tag{5}$$

$$(1-L)^{d5}Rnryoyt \tag{6}$$

Where *Rnrmomt* and *Rnryoyt* are the cointegrating residuals obtained by regressing stock market returns on the month-on-month inflation rate, and on the year-on-year inflation rate, respectively.

Presence of cointegration implies that there must be at least causality in one direction (Engle and Granger 1987). To test that, this study applied Granger causality using both first differenced and fractionally differenced data.

3.3 Granger causality using first differenced data

To investigate presence of short run as well as the long run causal effects between inflation rate and stock market returns, this study estimated the following standard Granger causality models (Engle and Granger 1987):

$$\left.\begin{aligned} \Delta NRt &= \varpi 0 + \sum_{j=1}^{m} K_{11}^{j}\Delta NRt{-}j + \sum_{j=1}^{n} K_{12}^{j}\Delta MOMt{-}j + \sigma o ECT1t{-}1 + \Im_{1t} \\ \Delta MOMt &= \varpi 1 + \sum_{j=1}^{m} K_{21}^{j}\Delta NRt{-}j + \sum_{j=1}^{n} K_{22}^{j}\Delta MOMt{-}j + \sigma 0 ECT1t{-}1 + \Im_{2t} \end{aligned}\right\} \tag{7}$$

$$\left.\begin{aligned} \Delta NRt &= \varpi 2 + \sum_{k=1}^{m} w_{11}^{k}\Delta NRt{-}k + \sum_{k=1}^{n} w_{12}^{k}\Delta YOYt{-}k + \sigma 1 ECT2t{-}1 + \Im_{3t} \\ \Delta YOYt &= \varpi 3 + \sum_{k=1}^{m} w_{21}^{k}\Delta NRt{-}k + \sum_{k=1}^{n} w_{22}^{k}\Delta YOYt{-}k + \sigma 1 ECT2t{-}1 + \Im_{4t} \end{aligned}\right\} \tag{8}$$

Where $ECT1t-1$ is the error correction term from regressing stock market returns on the month-on-month inflation rate lagged one period, and the other variables are as defined in Table 1. The optimal lag lengths were determined from the models with lowest Akaike Information Criterion (AIC).

Table 1 Description and measurement of variables

Variable name	Notation	Measurement
Monthly NSE 20 share index nominal returns	NR_t	Proxy for the Security Exchange's performance. Computed as percentage change in closing NSE 20 Share Index between successive months as: $NR_t = \ln\left(\frac{NSE_t}{NSE_t-1}\right) \times 100$, where NSE_t is the closing NSE 20 Share index at time t.
Month-on-Month inflation rate	MOM_t	Monthly percentage change in Consumer Price Index series computed as: $MOM_t = \ln\left(\frac{CPI_t}{CPI_{t-1}}\right) \times 100$ where CPI_t is the value of consumer price index at month t. MOM_t captures the short run inflation dynamics, has less variance and high forecast ability which could be helpful in portfolio adjustment.
Year-on-Year inflation rate	YOY_t	Is the yearly percentage change in the CPI series computed as: $YOY_{Jan2010} = \left(\frac{CPI_{Jan2010}}{CPI_{Jan2009}} - 1\right) \times 100$. YOY_t captures long run dynamics of inflation and has high variance and low forecast ability.

This table provides the names of the variables as well as the notations used to represent them. It also reports how the variables were constructed

3.4 Granger causality using fractionally differenced data

Most economic and financial time series such as stock market returns and inflation rate are neither nonstationary in levels nor stationary in first difference (Teyssiere and Kirman 2007). To capture this possibility of long memory, this study extended the concept of Granger causality to the more general fractionally integrated error correction model (FIECM).This is because the cointegrating residuals themselves might possess long memory (Caporin et al. 2013). The following Granger causality models were employed:

$$\left.\begin{array}{l}(1-L)^{d1}NRt = \varpi 4 + \sum_{i=1}^{m} p_{11}^{i}(1-L)^{d1}NRt-i + \sum_{i=1}^{n} p_{12}^{i}(1-L)^{d2}MOMt-i + \sigma 2fdRnrmomt-1 + \mathfrak{J}_{5t}\\ (1-L)^{d2}MOMt = \varpi 5 + \sum_{i=1}^{m} p_{21}^{i}(1-L)^{d1}NRt-i + \sum_{i=1}^{n} p_{22}^{i}(1-L)^{d2}MOMt-i + \sigma 2fdRnrmomt-1 + \mathfrak{J}_{6t}\end{array}\right\} \tag{9}$$

$$\left.\begin{array}{l}(1-L)^{d1}\mathrm{NRt} = \varpi 6 + \sum_{i=1}^{m} \phi_{11}{}^{i}(1-L)^{d1}NRt-i + \sum_{i=1}^{n} \phi_{12}{}^{i}(1-L)^{d3}YOYt-i + \sigma 3fdRnryoyt-1 + \mathfrak{J}_{7t}\\ (1-\mathrm{L})^{d3}\mathrm{YOYt} = \varpi 7 + \sum_{i=1}^{n} \phi_{21}{}^{i}(1-L)^{d1}NRt-i + \sum_{i=1}^{m} \phi_{22}{}^{i}(1-L)^{d3}YOYt-i + \sigma 3fdRnryoyt-1 + \mathfrak{J}_{8t}\end{array}\right\} \tag{10}$$

Where $fdRnryoyt-1 = (1-L)^{d5}Rnryoyt-1$ is the fractionally integrated error correction term (FIECT) derived from regressing stock market returns on the year-on-year inflation rate lagged one period, and $(1-\mathrm{L})^{d3}\mathrm{YOYt}$ is the fractionally differenced year-on-year inflation rate. The optimal number of lag lengths was chosen from models with the lowest AIC.

4 Data and sources

Table 1 provides the description and measurement of the variables. The study used monthly secondary time series data with the full sample period from 1st January 1993 to 31st December 2015 which yielded a total of 276 observations. The variables of the study comprised monthly NSE 20 Share index drawn from Nairobi Securities Exchange (NSE) as well as month-on-month inflation rate and year-on-year inflation rate obtained from the Kenya Bureau of Statistics (KEBS).

5 Results and discussion

5.1 Descriptive statistics

Table 2 presents the summary statistics of the stock market returns, month-on-month inflation rate and year-on-year inflation rate. The analysis was conducted for the whole sample period from 1st January 1993 to 31st December 2015.

Table 2 reveals that the mean values of all the variables are positive with the mean of the year-on-year inflation rate being much higher than that of the month-on-month inflation rate while that of stock market returns is the lowest. This suggests that higher values of both measures of inflation rate could have depressed the performance of the stock market. Furthermore, all the variables recorded excess positive kurtosis, suggesting that they individually posed lesser risk of extreme outcomes. Additionally, all the variables had positive skewness which implies that their actual values were likely to deviate further upwards from their mean values.

Furthermore, the wide range in the year-on-year inflation rate (see maximum of 61.54 versus minimum of −3.66) suggests that the variable rose significantly during the

Table 2 Summary descriptive statistics for the whole sample

	NR_t	MOM_t	YOY_t
Mean	0.45	0.77	10.54
Median	0.19	0.56	7.53
Maximum	41.81	7.7	61.54
Minimum	−25.67	−2.45	−3.66
Std. Dev.	6.83	1.37	10.81
Skewness	0.96	1.59	2.74
Kurtosis	9.65	8.62	11.03
Jarque-Bera	551.51	479.67	1087
Probability	0.00000	0.00000	0.0000
Sum	124.17	213.57	2908.33
Sum Sq. Dev.	12,819.48	515.73	32,123.47
Observations	276	276	276

NR_t is log difference of the NSE 20 Share Index, MOM_t is the month-on-month inflation rate, and $YOY_t$is the year-on-year inflation rate period. Likewise, the very large negative value of the minimum NSE 20 Share Index returns (see maximum of 41.815 versus minimum of −25.667) suggests that demand for the stock market returns might have decreased significantly over the period. The two developments suggest that investors in Kenya were not sheltered against inflationary pressures through higher stock market returns.

On the other hand, the month-on-month inflation rate appears to have been the least volatile which seems to support the preference often given to the variable by portfolio managers in the rebalancing of portfolios.

5.2 Univariate ARFIMA analyses: Fractional integration

Table 3 presents results from the selected ARFIMA (p, d, q) models for stock market returns, month-on-month inflation rate and year-on-year inflation rate described by eqs. 2, 3 and 4. The study fitted ARFIMA (p, d, q) model, ranging from ARFIMA (0, d, 0) to ARFIMA (3, d, 3), to each of the variables and obtained sixteen competing models. The study then selected the models with both significant AR and MA components, no autocorrelation in residuals and lowest AIC out of the sixteen competing models as the best models for each of the time series.

The study also carried out two sided hypotheses tests to verify if the individual variables were indeed fractionally integrated. It tested the null hypothesis of short memory ($H0 : d = 0$) against the alternative of long memory ($H1 : d \neq 0$) as well as the null hypothesis of permanent memory ($H0 : d = 1$) versus the long memory alternative($H1 : d \neq 1$). The tests were based on t test at 5% level of significance.

From the column for the ARMA (p, q), the results indicate that the selected ARMA (p,q) models for stock market return, month-on-month inflation rate and year-on-year inflation rate were (ARMA (2, 2), ARMA (3, 3) and ARMA (0, 3) respectively. This shows that only one variable, the year-on-year inflation rate (YOY), does not have the AR component while the rest contain both AR and MA components. It is therefore evident from Table 3 that the appropriate models for the individual variables include the AR and MA components. On average, higher order models or models with AR and MA parts of order 2 and above seem to be more suitable for modelling the variables except the model for the year-on-year inflation rate which excludes the AR part.

Table 3 Results of long memory estimates for the individual variables using EML

Variable notation	ARMA(p,q)	$\hat{d}$	$SE\left(\hat{d}\right)$	$tH0 : d = 0 = \frac{\hat{d}-d}{SE(\hat{d})}$	$tH0 : d = 1 = \frac{\hat{d}-d}{SE(\hat{d})}$
NR_t	(2,2)	0.231	0.05	4.37	−14.61
MOM_t	(3,3)	−0.590	0.18	−3.25	−5.83
YOY_t	(0,3)	0.494	0.01	55.5	−56.95

This table reports the ARFIMA estimates of the differencing parameters of the individual variables. It also provides the two hypotheses tests to determine whether the differencing parameters are significantly different from 1(one) and 0(zero) which indicates that the variables are indeed long memory processes

The long memory estimates were analysed at the 5% significance level (Gil-Alana 2001). NR_t is the log difference of the NSE 20 Share Index, MOM_t is the month-on-month inflation rate, and YOY_t is the year-on-year inflation rate

Moreover, there is no model where the white noise specification of the short memory components or ARMA (0, 0) is preferred.

The results also reveal that the estimated values of d parameter range from 0.231 to 0.59 (in absolute value) and none of the variables had short memory (*i. e.*, $d = 0$).This suggests that all the variables, though exhibiting different levels of persistence, returned to their equilibrium values after experiencing a shock. It further demonstrates that expected future increments or declines in the individual variables were predictable. This suggests that speculators could capitalize on this predictability to consistently make profits with no input of funds.

Furthermore, the results indicate that the year-on-year inflation rate was the most persistent (*i. e.*, $d = 0.494$)and reverted back to pre-shock level at the lowest rate. However, the negative sign for the d parameter associated with the month-on-month inflation rate indicates that higher values of the variable were often followed by lower values and lower values by higher values. This possibly explains the low standard deviation (volatility) revealed in Table 2. On the other hand, the positive sign of the d parameters for the year-on-year inflation rate and stock market returns suggests that increases in each of the variables were followed by increases whereas decreases triggered further decreases. Moreover, all the d parameters were significantly different from 0 and 1, based on the hypotheses tests. This implies that the null hypotheses of short memory and permanent memory were both rejected in favour of the long memory alternatives. This confirms that the individual variables were indeed long memory processes.

The results, however, contradict Balparda et al. (2015) and Anoruo and Gil-Alana (2011) who concluded that the NSE 20 Share index returns had an integer order of integration greater than 1, implying no mean reversion. The difference in the results might however be explained by the fact that while Balparda et al. (2015) and Anoruo and Gil-Alana (2011) used Robinson (1994, 1995) tests, this study employed the more superior EML procedure to estimate the integration orders (Dalhaus 2006; Miller and Miller 2003). The result of mean-reversion in stock market returns is however consistent with that established by Nazarian et al. (2014) who concluded that the stock market returns in Iran possessed stationary long memory.

5.3 Bivariate ARFIMA analysis: Fractional cointegration

Table 4 presents the results, including the hypotheses tests for the cointegrating residuals represented by eqs. 5 and 6. The study fitted ARFIMA models to the respective cointegrating residuals to determine whether each had an integration order lower than the integration orders of the parent time series (Caporin et al. 2013). It then selected the models with both significant AR and MA components, no autocorrelation in residuals and lowest AIC out of the sixteen competing models as the best models for each of the cointegrating residuals.

The study conducted two sided hypotheses tests to verify if the cointegrating residuals were indeed fractionally integrated. It tested the null hypothesis of short memory ($H0 : d = 0$) against the alternative of long memory ($H1 : d \neq 0$) as well as the null hypothesis of permanent memory ($H0 : d = 1$) versus the long memory alternative($H1 : d \neq 1$). The tests were based on t test at 5% level of significance.

Table 4 Hypotheses tests for d parameter for the cointegrating residual using EML

Cointegrating residual	ARMA(p,q)	$\hat{d}$	$SE\left(\hat{d}\right)$	$tH0:d=0=\frac{\hat{d}-d}{SE\left(\hat{d}\right)}$	$tH0:d=1=\frac{\hat{d}-d}{SE\left(\hat{d}\right)}$
$Rnrmom_t$	(2,2)	0.209	0.05	3.92	−14.8
$Rnryoy_t$	(2,2)	0.067	0.05	1.22	−17.02

This table reports the results of the differencing parameter estimates of the cointegrating residuals between the two measures of inflation rate and stock market returns

The long memory estimates are usually analysed at the 5% significance level (Gil-Alana 2001). $Rnrmom_t$ is the cointegrating residual from regressing stock market returns on the month-on-month inflation rate, and $Rnryoy_t$ is the cointegrating residual from regressing stock market returns on the year-on-year inflation rate

Clearly, results in Table 4 reveal that both cointegrating residuals are stationary non-integer processes. The differencing parameter d for *Rnrmomt* is significantly different from 0, which means the cointegrating residual is not a short memory process. The cointegrating residual is also significantly different from 1 which suggests that it is not a permanent memory process. Consequently, the study concluded that the cointegrating residual was indeed a long memory process. On the other hand, the differencing parameter (d) of the *Rnryoyt* is significantly different from one but not significantly different from 0. This suggests that while the null hypothesis of permanent memory is rejected, that of short memory cannot be rejected. Consequently, the study concluded that deviations of the year-on-year inflation rate and stock market returns from their long run equilibrium were corrected fairly fast but not as fast as is assumed under the conventional cointegration framework ($i.\ e., d = 0.067$ versus$d = 0$). The result therefore suggests that active policy intervention could be required to induce faster adjustment to equilibrium following any external shocks to stock market returns and the month-on-month inflation rate since the deviations are prolonged.

Besides, the d parameters of the cointegrating residuals are each less than the absolute values of the d parameters associated with the respective parent time series (refer to Table 3). This means that despite the individual variables having different non-integer orders of integration, a stable linear combination with a lower degree of non-integer order of integration does exist. Consequently, this study concluded that stock market returns are fractionally cointegrated with each of the measures of inflation rate (Caporin et al. 2013).

Whenever a cointegration is established between variables, there should be a causal relationship at least in one direction (Engle and Granger 1987). This study therefore employed the conventional ECM and extended the same to a Fractionally Integrated Error Correction Model (FIECM) to determine the direction of causality and speed of adjustment using both first differenced as well as fractionally differenced data. The FIECM model was adopted because it allows the cointegrating residual to have long memory or to be more persistent as opposed to the conventional assumption that deviations from the long run equilibrium dissipate quickly (i.e. the cointegrating residual is an I(0) process).

5.4 Granger causality tests using first and fractionally differenced variables

Table 5 provides a summary of the results from the ECM-based granger causality test represented by eqs. 7 and 8. It also contains results from the FIECM-based granger causality tests captured by eqs. 9 and 10.

Table 5 Estimates of granger causality using first and fractionally differenced data

Dependent variables	Sources of causation		
	NR_t	MOM_t	YOY_t
NR_t	–	**[−0.801]***** (0.318)	**[−0.916]***** (−0.0003)**
MOM_t	**[0.011]** (0.151)	–	
YOY_t	**[− 0.005]** (6.2e-06)		

This table reports the results of both conventional and ARFIMA-based Granger causality tests. The coefficients of the error correction terms lagged one period for the ECM-based granger causality models are in bold within parenthesis while those based on FIECM are in brackets

*** 1% significance level, ** 5% significance level, * 10% significance level. NR_t is log difference of the NSE 20 Share Index, MOM_t is the month-on-month inflation rate, YOY_t is the year-on-year inflation rate

The results demonstrate that based on the ECM, a unidirectional long run granger causality ran from the month-on-month inflation rate as well as from the year-on-year inflation rate to stock market returns. Table 5 further indicates that deviation of stock market returns and year-on-year inflation rate from their long run path was restored at the fastest rate of 92% per month. This is in line with the lowest level of persistence (i.e. $\hat{d} = 0.067$) reported in Table 4 for the associated cointegrating residuals.

Furthermore, results from the FIECM models in Table 5 reveal that the rate of convergence to long run equilibrium was much lower relative to that found by the ECM models. For instance, the FIECM model established that the year-on-year inflation rate and stock market returns converged to a long run equilibrium at a mere 0.03% per month compared to the rate of 92% indicated by the ECM model. This has significant policy implications since assuming that the readjustment rate is 92% while it is indeed 0.03 would result into prolonged deviations between the two variables and lead to undesirable economic conditions.

Table 6 presents more detailed results from the ECM-based and FIECM-based granger causality tests captured in Eqs. 7, 8, 9 and 10.

The ECM-based results in Table 6 reveal that the year-on-year inflation rate positively granger caused stock market returns in the long run (see coefficient of lagged first difference of *YOYt* in Panel C). In contrast, a negative long run causality originated from the month-on-month inflation to stock market returns rate (see coefficient of lagged first difference of *MOMt* in Panel A). These results suggest that whereas the stock market in Kenya does not cushion investors against inflationary pressures in the short run, investors with long investment horizons benefit from increments in stock market returns in response to rising inflation rates. In other words, the stock market in Kenya provides shelter to investors against inflationary pressures in the long run (Fisher 1930; Alagidede and Panagotidis 2010; Ochieng and Adhiambo 2012).

However, Table 6 shows that the ECM-based tests did not find short run causality between either of the measures of inflation rate and stock market returns. This implies that the Kenyan stock market does not suffer from inflation risk in the short run. The results support Kirui et al. (2014) but contradict Ouma and Muriu (2014) as well as Kimani and Mutuku (2013).

Table 6 Bivariate granger causality for stock market returns and inflation rate

	First differenced model			Fractionally differenced model		
	Coefficient	Std. Error	t-ratio	Coefficient	Std. Error	t-ratio
Panel A: Estimation results of stock market returns (NR_t)on short term inflation rate (MOM_t)						
Intercept	−0.034	0.393	−0.086	0.125	0.386	0.325
dMOMt-1	−0.326	0.359	−0.908	0.230633	0.565	0.408
dMOMt-2	−0.262	0.373	−0.702	0.148	0.406	0.364
dMOMt-3	−0.97	0.447	−2.173**	−0.757	0.456	−1.659*
Rnrmomt-1	−0.801	0.142	−5.637***	0.318	0.679	0.467
dNRt-1	0.062	0.125	0.501	−0.285	0.710	−0.402
dNRt-2	0.013	0.066	0.192	−0.04	0.161	−0.275
Panel B: Estimation results of short term inflation rate (MOM_t) on stock market returns (NR_t)						
Intercept	−0.032	0.064	−0.505	0.019	0.062	0.301
dNRt-1	0.001	0.011	0.041	−0.143	0.084	−1.691*
dNRt-2	0.019	0.012	1.622	0.062	0.029	2.106**
Rnrmomt-1	0.011	0.013	0.868	0.151	0.084	1.780*
dMOMt-1	−0.409	0.082	−5.012***	−0.044	0.093	−0.469
dMOMt-2	−0.304	0.059	−5.177***	−0.069	0.104	−0.664
dMOMt-3	−0.204	0.077	−2.661***	−0.094	0.067	−1.392
Panel C: Estimation results of stock market returns(NR_t) on long term inflation rate (YOY_t)						
Intercept	0.035	0.403	0.087	−0.054	0.349	−0.155
dYOYt-1	0.195	0.198	0.984	0.277	0.110	2.521**
Rnryoyt-1	−0.916	0.153	−5.994***	−0.0003	0.0001	−1.965*
dNRt-1	0.124	0.162	0.763	0.014	0.116	0.116
dNRt-2	0.055	0.089	0.616	−0.164	0.099	−1.661*
Panel D: Estimation results of long term inflation rate (YOY_t) on stock market returns (NR_t)						
Intercept	−0.054	0.133	−0.408	0.02	0.119	0.168
dYOYt-1	0.329	0.106	3.099***	0.788	0.064	12.291***
dNRt-1	0.003	0.029	0.118	0.003	0.021	0.153
dNRt-2	0.036	0.023	1.557	0.037	0.021	1.782*
Rnryoyt-1	−0.005	0.039	−0.126	6.15e-06	3.76e-05	0.163

This table reports the detailed results of bivariate Granger causality tests between each of the measures of inflation rate and stock market returns

Heteroscedasticity and autocorrelation consistent (HAC) standard errors were used to obtain more efficient parameter estimates. *** 1% significance, ** 5% significance * 10% significance level

On the contrary, the FIECM-based models demonstrate that a positive short run unidirectional granger causality originated from the year-on-year inflation rate to stock market returns (see coefficient of lagged fractionally differenced of *YOYt* in Panel C). This supports the Fisher Effect (Fisher 1930) and implies that past values of the year-on-year inflation rate have predictive power on future values of stock market returns in Kenya. This also means that investors in the Kenyan stock market get compensated during inflationary periods through higher stock market returns in the short run.

6 Conclusion

The purpose of this study was to establish the relationship between inflation rate and stock market returns in Kenya, and also to examine the long memory properties of the individual time series and their cointegrating residuals. The study employed the ARFIMA-based exact maximum likelihood (EML) estimation technique to empirically determine the integration orders of the individual variables and those of the cointegrating residuals. The study also conducted conventional Granger causality and extended the same to an ARFIMA-based Granger causality test to examine causal relationships between the two measures of inflation rate and stock market returns.

The ARFIMA-based EML estimation revealed that the differencing parameters for all the individual variables were non-integer values less than 1 and significantly different from 0 and 1. The study also established that the cointegrating residuals between stock market returns and the month-on-month inflation rate had a non-integer order of integration less than 1 and significantly different from 1 and 0. However, the cointegrating residuals between stock market returns and the year-on-year inflation rate had a non-integer order of integration less than 1, significantly different from 1 but not from 0.

In conclusion, the ARFIMA models show that stock market returns, inflation rate and their cointegrating residuals behave differently from the stationary or integrated processes that have been assumed in most studies using data from Kenya. This suggests that the relationship between stock market returns and inflation rate in Kenya might be more complex than has been explained by existing literature. This fact has several important implications for policy design and implementation and for further studies.

First, the results imply that long memory plays an important role in the structure and dynamic behaviour of the Kenyan stock market and must be influencing the investment strategies of foreign investors as well as those of multinational portfolio holders (who constitute over 50% of investors at the NSE, Ndwiga and Muriu 2016). Second, the presence of long memory in the stock market returns suggests that there is either high persistence of risk factors or poor liquidity in the Kenyan stock market. Consequently, investors may be exploiting such inefficiencies to earn excess returns without bearing additional risks.

Third, the presence of long memory implies that shocks affecting stock market returns and inflation rates in Kenya have long lasting but decreasing effects over time. However, the presence of long memory in the cointegrating residuals suggests that deviations of stock market returns from inflation rates take longer to dissipate. This further implies that appropriate policy actions are required to reestablish long term equilibria whenever shocks drive the two variables apart.

Moreover, the presence of long memory suggests that a miss-specified economic policy may be more devastating than no policy action. This therefore implies that policymakers and researchers in Kenya need to employ nonlinear econometric models such as the ARFIMA models in order to obtain more efficient price forecastings. In particular, investors, policymakers and financial practitioners need to be extra cautious while applying the standard statistical inferences and asset pricing models such as CAPM. This is because these analytical procedures are based on the assumptions that the variables have normal distributions and short memory.

The results of this study also suggest that researchers and the stock market regulator (in this case, the Capital Market Authority) need to re-examine the likely sources of the persistence that is being exhibited in the form of long memory in order to improve the efficiency of the Kenyan stock exchange. The results equally imply that future studies should focus on estimating the correct order of integration of the stock market returns, the determinants of stock market returns and the respective cointegrating residuals instead of assuming stationarity or unit root behaviour of the individual variables or the conventional cointegration between stock market returns and the determinants.

Finally, this study has not incorporated structural breaks in the estimating models. However, short memory with structural breaks may spuriously reflect long memory (Granger and Hyung 2004). Further study should therefore consider investigating presence of structural breaks in the Kenyan stock market returns and inflation rates.

References

Ada AM, Osahon IS (2015) Stock returns, inflation and the "reverse causality" hypothesis: evidence from Nigeria. International Journal of Research in Business and Soc Sci 4(1):32–50

Alagidede P, Panagotidis T (2010) Can common stocks provide a hedge against inflation? Evidence from African countries. Rev Financ Econ 19:91–100. https://doi.org/10.1016/j.rfe.2010.04.002

Anoruo E, Gil-Alana L (2011) Mean reversion and long memory in African stock market prices. J Econ Financ 35(3):296–308. https://doi.org/10.1007/s12197-010-9124-0

Aye GC, Balcilar M, Gupta R, Kilimani N, Nakumuryango A, Redford S (2012) Predicting BRICS stock returns using ARFIMA models. University of Pretoria Working Paper 35:1–23

Balparda B, Caparole GM, Gil-Alana LA (2015) The Kenyan stock market: inefficiency, long memory, persistence and Anomalities in the NSE-20. African Journal of Economic and Sustainable Development 4(3):251–277. https://doi.org/10.1504/AJESD.2015.071911

Cakan E, Ejara DD (2013) On the relationship between exchange rates and stock prices: Evidence from emerging markets. International Research Journal of Finance and Economics (111):115–124

Caporin M, Ranaldo A, Santucci de Magistris P (2013) On the predictability of stock prices: a case for high and low prices. J Bank Financ 37(12):5132–5146. https://doi.org/10.1016/j.jbankfin.2013.05.024

Chen NF, Roll R, Ross S (1986) Economic forces and the stock market. J Bus 59(3):383–403. https://doi.org/10.1086/296344

Cheung Y-W, Lai KS (1993) A fractional Cointegration analysis of purchasing power parity. J Bus Econ Stat 11(1):103–112. https://doi.org/10.1080/07350015.1993.10509936

CMA Quarterly Capital Markets Statistical Bulletin-Q1 (2017) Kenya's Capital Market Authority's Statistical Bulletin- First Quarter of 2017

Dalhaus R (2006) Correction efficient parameter estimation for self-similar processes. Ann Stat 34(2):1045–1047. https://doi.org/10.1214/009053606000000182

Dasgupta R (2012) Long-run and short-run relationships between BSE Sensex and macroeconomic variables. International Research Journal of Finance and Economics 95:135–150

Demirhan B (2016) Revisiting the fisher hypothesis: evidence from Turkey based on the methods of FMOLS, DOLS and CCR. *Asian Academic Research*. Journal of Social Science and Humanities 3(4):318–335

Engle R, Granger C (1987) Cointegration and error correction: representation estimation, and testing. Econometrica 55(2):251276. https://doi.org/10.2307/1913236

Erita JH (2014) Interest rate and stock market returns in Namibia. International Business & Economics Research Journal 13(4):689–696

Fama EF (1981) Stock returns, real activity, inflation and money. Am Econ Rev 71(4):545–556

Fisher I (1930) The theory of interest rate. McMillan, New York

Frimpong S (2011) Speed of adjustment of stock prices to macroeconomic information: evidence from Ghanaian stock exchange (GSE). International Bus Manag 2(1):151–156

Geske R, Roll R (1983) The fiscal and monetary linkage between stock returns and inflation. J Financ 38(1): 1–33. https://doi.org/10.1111/j.1540-6261.1983.tb03623.x

Gil-Alana LA (2001) Testing of stochastic cycles in macroeconomic time series. J Time Ser Anal 22(4):411–430. https://doi.org/10.1111/1467-9892.00233

Granger CWJ, Hyung N (2004) Occasional structural breaks and long memory with application to the S&P 500 absolute returns. J Empir Financ 11(3):399–421

Granger CWJ, Joyeux R (1980) An introduction to long memory time series models and fractional differencing. J Time Ser Anal 1(1):15–29. https://doi.org/10.1111/j.1467-9892.1980.tb00297.x
Gohar AH, Zaman G, Baloch OB (2014) The causal relationship of interest rate and stock prices: Empirical evidence from Pakistani markets. City University Research Journal 4(2):147–155
Gupta RD, Modise MP (2013) Macroeconomic variables and south African stock return predictability. Econ Model 30:612–622. https://doi.org/10.1016/j.econmod.2012.10.015
Hamrita ME, Trifi A (2011) The relationship between interest rate, exchange rate and stock price: a wavelet analysis. International Journal of Economics and Financial Issues 1(4):220–228
Hautcoeur, P.C. (2011). Why and How to Measure Stock Market Fluctuations? The Early History of Stock Market Indices, with Special Reference to the French Case. Working Paper No. 2006–10
Hosking JRM (1981) Fractional differencing. Biometrika 68(1):165–176. https://doi.org/10.1093/biomet/68.1.165
Jawaid ST, Anwar UH (2012) Effects of interest rate, exchange rate and their volatilities on stock prices: Evidence from banking industry of Pakistan. Theoretical and Applied Economics 19(8):153–166
Issahaku H, Ustarz Y., and Domanban P.B. (2013). Macroeconomic variables and stock market returns in Ghana: any causal link? Asian Economics and Financial Review 3(8), 1044–1062
Kim JH, Ryoo HH (2011) Common stocks as a hedge against inflation: evidence from century-long US data. Econ Lett 113:168–171. https://doi.org/10.1016/j.econlet.2011.07.003
Kimani DK, Mutuku CM (2013) Inflation dynamics on the overall stock market performance: the case of Nairobi securities exchange in Kenya. Economics and Finance Review 2(11):1–11
Kiran B (2011) Fractional cointegration relationship between oil prices and stock markets: An empirical analysis from G7 countries. Journal of Prague Economic Papers 2:177–189. https://doi.org/10.18267/j.pep.395
Kirui E, Wawire HWN, Onono PO (2014) Macroeconomic variables, volatility and stock market returns: a case study of Nairobi securities exchange, Kenya. International Journal of Economics and Finance 6(8):214–228. https://doi.org/10.5539/ijef.v6n8p214
Lo AW, Campbell JY, Mackinlay AC (1997) The econometrics of financial markets. Princeton University, New Jersey
Miller I, Miller M (2003) John E. Freund's mathematical statistics with applications, 7ED. Pearson Education, New Jersey
Nairobi Securities Exchange (2010) Annual Reports
Nazarian R, Naderi E, Alikhani NG, Amiri A (2014) Long memory analysis: an empirical investigation. *International Journal of Economics and Financial Iss*ues 4(1):16–26
Ndwiga D, Muriu PW (2016) Stock returns and volatility in an emerging equity market. Evidence from Kenya. European Scientific Journal 12(4):79–98
Ochieng DE, Adhiambo EO (2012) The relationship between macroeconomic variables and stock market performance in Kenya. DBA Africa Manag Rev 3(1):38–49
Okunev J, Wilson P (1997) Using nonlinear tests to examine integration between real estate and stock markets. Real Estate Econ 25(3):487–503. https://doi.org/10.1111/1540-6229.00724
Ouma WO, Muriu PW (2014) The impact of macroeconomic variables on stock market returns in Kenya. International Journal of Business and Commerce 3(11):01–31
Pal K, Mittal R (2011) Impact of macroeconomic indicators on Indian capital markets. Journal of Risk Finance 12(2):84–97. https://doi.org/10.1108/15265941111112811
PwCIL (2017): PricewaterCoopers International Limited report of 2017
Robinson PM (1994) Efficient tests of nonstationary hypotheses. J Am Stat Assoc 89(5):1420–1437. https://doi.org/10.1214/aos/1176324317
Rushdi M, Kim JH, Silvapulle P (2012) ARDL bounds tests and robust inference for the long run relationship between real stock returns and inflation in Austrialia. Econ Model 29:535–543. https://doi.org/10.1016/j.econmod.2011.12.017
Sowel F (1992) Maximum likelihood estimation of stationary univariate fractionally integrated time series models. J Econ 53(1):165–188. https://doi.org/10.1016/0304-4076(92)90084-5
Teyssiere G, Kirman AP (2007) Long memory in economics. Springer Berlin Heidelberg, New York
Yartey CA, Adjasi CK. 9 (2007) Stock Market Development in Sub-Saharan Africa: Critical Issues and Challenges. IMF Working Paper 07/209