Time-series modeling of returns from the NSE 20-share index: An empirical study of the impact of political climate on market volatility

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Abstract

A time series analysis of the Nairobi Stock Exchange (NSE) 20-Share index from January 1998 to March 2007 is provided. A comparison of the daily rates of return and volatilities for periods immediately preceding and following election years (2002-2003) and periods prior to and after this electoral season (1998-2001 and 2004-2006). Volatility, as measured by the absolute change in the rate of return, has positive serially correlations in the markets as expected. This paper also tests whether the efficient market hypothesis (EMH) hold in the case of the NSE 20 share index. The results indicate that this hypothesis is not satisfied as in this paper both the ARIMA(1,1,1) and the GARCH(1,1) models are fit to the data. The random walk process that holds under the EMH does not hold for this data. Prediction for the NSE index for a range of periods is given.

KEY WORDS : *Time series analysis; Autoregressive integrated Moving Average (ARIMA) process; Generalised Autoregressive Conditional Heteroskedastic (GARCH) process; Rate of return; Volatility; Autocorrelation function (ACF); Partial Autocorrelation function (PACF); Nairobi Stock exchange (NSE).*

Introduction

World over a stock exchange index is assumed to be an indicator of the economical, social and political volatility of a nation. Therefore when the economy of a country is thriving and the political environment is stable, the stock exchange index is high. Share stocks are a form of investment. Investors buy shares at a certain price hoping that the share price of a stock will increase in future enabling them make profits. These share prices are expected to be determined by the basic market principle of supply and demand. However this is not normally the case. Various other factors are seen to influence the prices of stock. These include, government policy as seen in the US farm policy by Sergio 'et al' (2002), increased international influence as researched by John (1999), transaction costs and securities transaction taxes as implicitly seen by Allen "et al"(1997). Most of the above factors hinge on availability of information or speculation as normally refered to in the stock exchange environments. Using the Kenyan stock exchange scenario in the past ten years, this paper postulates to illustrate how information affects the changes in prices of stock at the Nairobi Stock exchange in line with the efficient market hypothesis.

Background

December 2002 marked the end of a 40 year Kenya African National Union (KANU) rule in Kenya. The last 10 years of KANU's rule saw the re-establish and strengthening of multi-party politics in Kenya, a clamor for a new constitutional dispensation and increase public demand for perpetrators of grand corruption to be brought to book.

The optimism that surrounded the election of a National Rainbow coalition (NARC) government was short-lived as immediately after the new government took office, cries of dissatisfaction were heard. The government, however, reduced domestic borrowing, introduced stringent tax collection measures, and went on to inspire local and international investor confidence. These measures led to an economy recovery from a zero growth rate in 2001 to a seven percent growth rate in 2007. This period saw the Nairobi Stock Exchange, established in 1954, attract local and international investor interest.

The post-election crisis that followed the December 2007 general election in Kenya, deep-rooted ethnically issue and perceived socio-economic disparities, threatened to nullify the gains made in the 5 years of the NARC. The campaign period only served to excite ethnic tension and made it difficult for businesses to thrive and for the economy to attract or inspire both local and/or international investment.

This paper is to study the characteristics of the Nairobi Stock Exchange (NSE) index from January 1998 to March 2007. The paper also attempts to evaluate whether market index satisfies the efficient market hypothesis, to determine, estimate and interpret, an appropriate a Garch*(p,q)* model to the NSE 20-share index and to compare the volatility of the market during pre and post-election years. We also compare the performance of the market index during periods of relative electoral calm and periods immediately prior to or after an election.

The efficient market hypothesis

Ross (1987) states that a market is efficient with respect to a set of information if it is impossible to make economic profits by trading on the basis of this information set and that consequently no arbitrage opportunities, after costs, and after risk premium can be tapped using ex ante information as all the available information has been discounted in current prices.

Müslümov *et al (*2004) noted that capital markets with higher informational efficiency are more likely to retain higher operational and allocational efficiencies.

According to Samuelson (1965) and Fama (1970), under the 'efficient market hypothesis' (EMH), stock market prices must always show a full reflection of all available and relevant information and should follow a random walk process. Successive stock price changes (returns) are therefore independently and identically distributed (*iid*). Based on the information set, Fama (1970) categorizes the three types of efficient markets as weak-form, semi-strong-form, and strong-form efficient if the set of information includes past prices and returns only, all public information, and any information public as well as private, respectively. The implication here is that all markets can be weak-form but the reverse cannot be the case.

Furthermore, stock market returns unlike other economic time-series, typically exhibit a set of peculiar characteristics such as clusters or pools of volatility and stability (i.e. large changes in these returns series tend to be followed by large changes and small changes by small changes) Mandelbrot (1963) and Fama (1965), and leptokurtosis, (i.e. the distribution of returns tends to be fat-tailed) Fama (1965).

Methodology

Data

The data, y_t, for this paper were daily NSE 20-share index from January 1998 to March 2007. Using the **Splus** *finmetric* package, daily returns, r_t, were calculate as follows:

$$r_t = \ln\left(\frac{y_t}{y_{t-1}}\right) \quad (0.1)$$

Generalised heteroskedastic conditional heteroskedastic (Garch) modeling

In this paper we fit a Garch *(1,1)* process to daily returns on the NSE 20-share index.

A stochastic process $r_t = c + \phi r_t + \varepsilon_t + \theta\varepsilon_{t-1}$, is Garch *(p,q)* if $\text{var}_{t-1}(\varepsilon_t) = \sigma_t^2$, with $\text{var}_{t-1}(.)$ denoting the conditional variance on information at time $t-1$, $\varepsilon_t = z_t\sigma_t$, and $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$, where z_t are independent and identically distributed random variables with zero mean.

Before fitting Garch *(1,1)* models to each of the daily returns series we first test for the presence of ARCH effects in the residuals. A stochastic process $y_t = c + \varepsilon_t$, is said to be Arch *(p)* if $\text{var}_{t-1}(\varepsilon_t) = \sigma_t^2$, $\varepsilon_t = z_t\sigma_t$, and $\sigma_t^2 = \omega + \sum_{i=1}^{q}\theta_i\varepsilon_{t-i}$.

If there does not exist a significant ARCH effect in the residuals then the ARCH model is unnecessary or mis-specified. Testing the hypothesis of no significant ARCH effects is based on the Lagragian Multiplier (LM) approach, where the test statistic is given by

$$LM = nR^2, \quad (0.2)$$

where n is the sample size and R^2 is the coefficient of determination for the regression in the ARCH model using the residuals.

Model Identification

To identify the GARCH *(1,1)* model that best explains returns for the NSE data we determine the Bayesian information criterion (abbreviated BIC) values for the following candidate Garch models:

Model 1: $r_t = c + \varepsilon_t$, $\varepsilon_t = z_t\sigma_t$, and $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$, where $z_t \sim WN(0, \sigma_t^2)$.

Model 2: $r_t = c + \varepsilon_t + \theta\varepsilon_{t-1}$, $\varepsilon_t = z_t\sigma_t$, and $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$, where $z_t \sim WN\left(0, \sigma_t^2\right)$.

Model 3: $r_t = c + \phi r_t + \varepsilon_t$, $\varepsilon_t = z_t\sigma_t$, and $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$, where $z_t \sim WN\left(0, \sigma_t^2\right)$.

Model 4: $r_t = c + \phi r_t + \varepsilon_t + \theta\varepsilon_{t-1}$, $\varepsilon_t = z_t\sigma_t$, and $\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$, where $z_t \sim WN\left(0, \sigma_t^2\right)$.

The model with the lowest BIC value is viewed as the best fitting model. The BIC statistic is given as

$$\text{BIC} = -2\ln(L) + k\ln(n), \tag{0.3}$$

where L denotes the maximized value of the likelihood function for the estimated model, k represents the number of free parameters to be estimated and n is the number of observations.

Exploratory analysis

In this section we use graphical techniques to identify possible patterns that exist in the NSE data. Based on this exploration we attempt to identify an appropriate model for the data.

Figure 1 Time-series plot the daily NSE 20-share index from January 1, 1998 to March 21, 2007

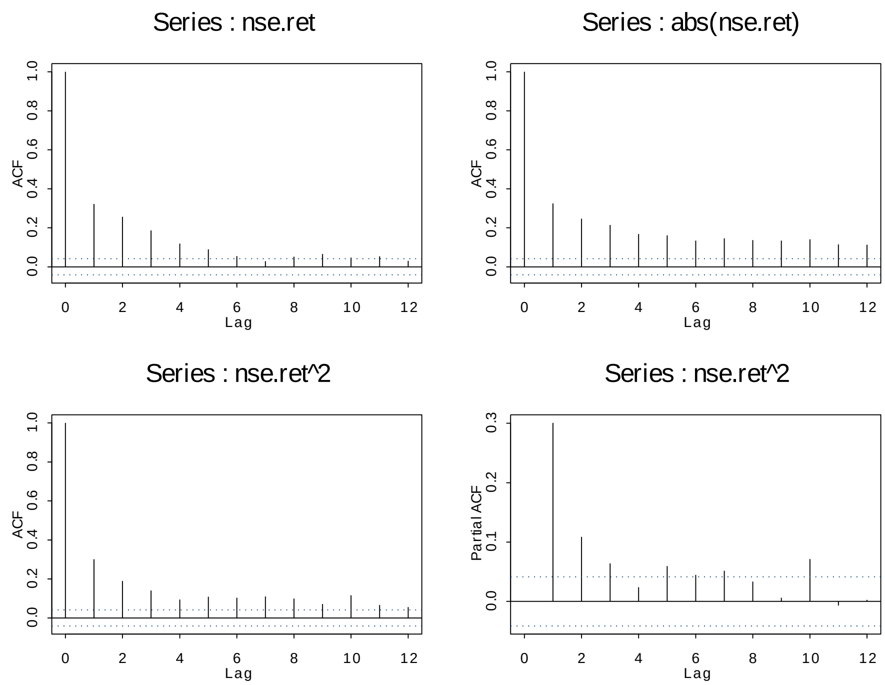

Figure 2 Sample ACF and PACF of various functions of daily log stock returns of the NSE 20-Share index from January 1, 1998 to March 21, 2007: (a) ACF of the log returns, (b) ACF of the squared returns (lower left), (c) ACF of the absolute returns (upper right), and (d) PACF of the squared returns.

From Figure 1, the market index exhibits a decline from a relative high value in 1998 to an all-time low that was experienced in late 2002. The market index from that point exhibits a steady growth that may be explained by the positive investor confidence experienced during the NARC era.

Figure 2 illustrates 4 important plots of the market index. The upper left plot is an ACF plot of the index, which indicates significant serial correlations and also the fact that the index exhibits some form of non-stationarity. The upper right and lower left plots are the ACF's of the absolute and squared returns, respectively. These plots suggest that the daily returns are not independent. These plots indicate that the returns are serially correlated and dependent.

Summary statistics

Summary statistics for the NSE return series are presented in Table 1. The mean continuously compounded return for the NSE is *0.019(±0.767).* The results indicate high volatility and the risky nature of the market since the standard deviation of the market returns is high in comparison with the mean.

Table 1 Descriptive statistics for the NSE return series

	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis
NSE index (1998-2007)	0.0193	0.7674	-4.949	4.831	0.1101	9.388
NSE index (1998-2001)	-0.0861	0.6342	-4.829	4.95	-0.4969	13.82
NSE index (2002-2003)	0.1463	0.972	-4.017	4.757	0.464	7.725
NSE index (2004-2006)	0.0995	0.7124	-2.67	3.912	0.3229	6.413

Table 2 Summary statistics for Annual NSE returns

	N	mean	abs(mean)	Std. Dev	Skewness	Kurtosis	Min	Max
1998	203	-0.022	0.02183	0.8471	0.259	11.21	-3.991	4.95
1999	245	-0.102	0.1015	0.5771	-1.326	9.473	-2.926	1.919
2000	253	-0.074	0.07421	0.6052	-1.841	17.54	-4.829	1.59
2001	242	-0.136	0.1355	0.4978	-0.1761	6.18	-2.374	1.974
2002	248	0.004	0.00438	0.7218	0.6129	6.469	-2.615	3.446
2003	248	0.288	**0.2883**	1.154	0.1811	6.673	-4.017	4.757
2004	253	0.030	0.0299	0.7923	0.7086	7.001	-2.404	3.912
2005	241	0.122	0.1223	0.6248	-0.07113	7.582	-2.67	3.089
2006		0.144	0.1435	0.7045	0.1384	4.507	-2.194	2.628
2007	56	-0.290	**0.2903**	1.122	-0.5057	3.141	-3.067	1.871

ARIMA(p,d,q) modeling

Table 3 AIC values for the candidate ARIMA*(p,d,q)* models

Model	AIC
AR(1)	4884.23
MA(1)	4996.86
ARMA(1,1)	4814.91
ARIMA(1,1,0)	5290.03
ARIMA(0,1,1)	4991.84
ARIMA(1,1,1)	**4868.18**

Based on the AIC values presented in Table 3, the *ARIMA(1,1,1)* model is identified to be the one that best fits the daily returns on the NSE 20-share index from January 1998 to March 2007. The equation of the *ARIMA(1,1,1)* model identified is given as

$$\Delta r_t = 0.28(\pm 0.02)\Delta r_{t-1} + \varepsilon_t + 0.98(\pm 0.005)\varepsilon_{t-1}. \tag{0.4}$$

Garch (p,q) modeling

Table 4 *Lagragian Multiplier test for Arch effects*

Returns	Chi-square	df	p-value
NSE index (1998-2007)	633.68	12	<0.001
NSE index (1998-2001)	9.16	12	0.689
NSE index (2002-2003)	111.72	12	<0.001
NSE index (2004-2006)	73.01	12	<0.001

From Table 4, significant arch effect in the daily returns on the NSE 20-share index for the January 1, 1998 to March 21, 2007 period detected. The results also indicate a significant arch effect in the NSE 20-share index for the period spanning January 2002 to December 2003 and for the period thereafter, spanning January 2004 and December 2006.

Table 5 Model selection

Model	AIC	BIC	p
Model 1	4662.345	4685.205	4
Model 2	4602.53	4631.10	5
Model 3	4575.84	4604.42	5
Model 4	4501.25	4535.54	6

From Table 5, it is noted that model 4 is the best fitting model. The Garch (1,1) model obtained is thus

$$r_t = -0.008(\pm 0.006) + 0.79(\pm 0.04) r_{t-1} + \varepsilon_t - 0.57(\pm 0.05)\varepsilon_{t-1}, \text{ and}$$

$$\sigma_t^2 = 0.032(\pm 0.003) + 0.135(\pm 0.01)\varepsilon_{t-1}^2 + 0.811(\pm 0.01)\sigma_{t-1}^2.$$

From the volatility equation, the implied unconditional variance of ε_t is

$$\operatorname{var}(\varepsilon_t \mid F_{t-1}) = \frac{0.03}{1-0.135-0.811} = 0.556. \tag{0.5}$$

Figure 3 and Figure 4 respectively, provides the sample ACF of the standardized shocks ε_t and the squared process ε_t^2. These ACFs fail to suggest any significant serial correlations in the two processes.

More specifically, we have the values of the Lagrange multiplier and Ljung-Box statistic as $Q(12) = 16.46(0.1711)$ and $Q(12) = 7.91(0.7921)$ for ε_t, , and also these statistics $Q(10) = 8.83(0.55)$ and $Q(20) = 15.82(0.73)$ for ε_t^2, where the number in parentheses is the *p* value of the test statistic. Thus, the model appears to be adequate.

Note that the fitted model shows $\alpha_1 + \beta_1 = 0.946$, which is close to 1. This indicates a covariance stationary model with a high degree of persistence in the conditional variance.

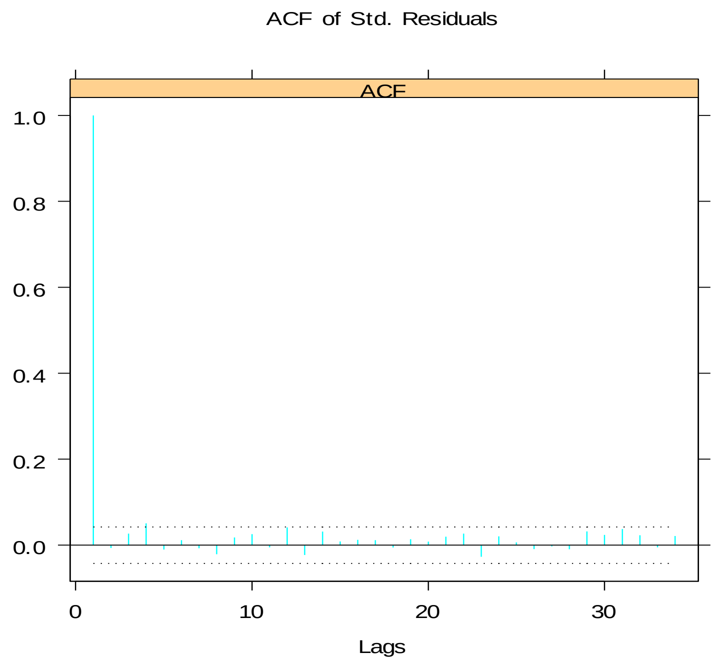

Figure 3 Autocorrelation plot for the residuals of the best fitting GARCH (1,1) model

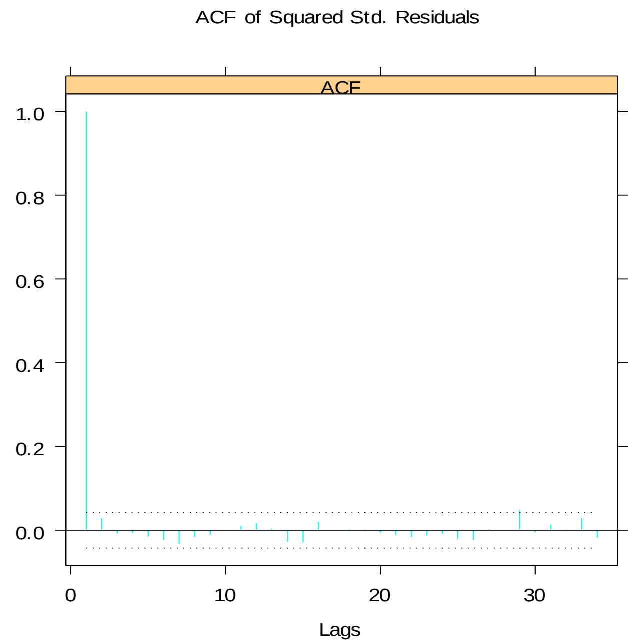

Figure 4 Autocorrelation plot for the squared studentised residuals of the best fitting GARCH (1,1) model

Discussion

Table 3 gives forecasts of the nse index for a period of 3- 7 months in the year 2008. This is more or less the scenario that has been seen in the Kenyan markets in the past few months until the global slum in October 2008. The high volatilities seen just before election periods indicates lack of information or uncertainty leads to low stock exchange index. More research needs to be done to determine the right information the investors need to be given to be boost their investment confidence.

In this paper we use both the Box-Jenkins (ARIMA) modeling approach and the GARCH approach to model returns from the NSE 20-share index. A comparison of the AIC and BIC values for these models reveals that the Garch model identified provides a better explanation of the dynamics of the market returns.

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