VOLATILITY ESTIMATION OF STOCK PRICES USING THE GARCH METHOD

BY

KIBIWOTT KOIMA

KABARAK UNIVERSITY

3RD INTERNATIONAL CONFERENCE

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- GENERALIZED- more general than ARCH model
- AUTOREGRESSIVE-depends on its own past
- CONDITIONAL-variance depends upon past information
- HETEROSKEDASTICITY- fancy word for non-constant variance

VOLATILITY

- This is a degree of fluctuations in asset prices
- Variability or randomness of asset price
- Volatility may also be described as the rate and magnitude of price changes which is referred to as a risk in finance.

RISK

- A Risk is a bad future event that might happen.
- Some risks can be avoided completely.
- But some risks are worth taking because the possible benefit exceeds the possible costs.
- Finance investigates which risks are worth taking.

What makes Volatility High in a Financial Market

- High Inflation
- Slow output growth and recession
- High volatility of short term interest rates
- High volatility of output growth
- High volatility of inflation

- Small or undeveloped financial markets
- Large countries

INTRODUCTION

- Volatility forecasting in financial market is very significant particularly in Investment, financial risk management and monetary policy making Poon and Granger (2003).

- Because of the link between volatility and risk, volatility can form a basis for efficient price discovery.

INTRODUCTION

- Modeling of time-varying conditional variance with Autoregressive Conditional Heteroskedasticity (ARCH) process was proposed by Engle, (1982) using lagged disturbance. The results obtained from this work indicate that in order to capture the dynamic behaviour of conditional variance, a high order ARCH model is required. This problem was solved by Bollesrslev, (1986) by developing a Generalized ARCH model (GARCH) basing on infinite ARCH specifications wich reduces the number of estimated parameters from infinity to two.

INTRODUCTION

- Volatility implying predictability is very important phenomenon for traders and medium term - investors.

- Equilibrium prices derived from change in volatility affects Asset pricing models and derivatives valuation which actually depends on a reliable volatility forecast.

INTRODUCTION

- Both ARCH and GARCH model capture volatility clustering and lepkurtosis but they fail to model leverage effects because their distribution is symmetric. To address this problem many non-linear extension of GARCH has been proposed such as the exponential GARCH (EGARCH) model by nelson, (1991) and also Asymmetric Power ARCH (APARCH) modeled by Ding et al, (1993). Another problem encountered when using GARCH is that they do not always fully embrace the thick tails property of a high frequency financial time series data.

INTRODUCTION

- Hansen and Lunde 2005) argued that GARCH (1, 1) works quite well in estimating volatility of financial returns as compared to more complicated models.In modeling volatility of Chinese stock market, Hung-Chung et al.(2009) showed that GARCH model with an underlying leptokurtic asymmetric distribution has better forecasting ability as compared to an underlying normal distribution. Wilhemsson (2006) using GARCH (1, 1) model with a fat tail error distribution leads to an improvement in a Volatility forecast.

INTRODUCTION

- Volatility and forecasting market risks from observations from Egypt (CMA and general index) and Israel (TASE-100 Index) was modeled using GARCH by Floros, (2008). It was found that Eyptian CMA Index is the most volatile series due to prices (and economy) uncertainity during the time period under consideration.
- Volatility clustering, excess kurtosis and heavy tails of time series of KSE using ARCH and GARCH was studied Rafique and Kashif-ur-Rehman, (2011).

OBJECTIVE

- The main objective of this study is to estimate the conditional volatility of stock market returns (equities) of Barclays Bank of Kenya consisting of 1023 observations data running from 1st Jan 2008 to 10th Oct 2010 using the GARCH Method.

METHODOLOGY

The GARCH (p, q) model is given by

$$\begin{cases} Y_t = \mu + \sigma_t \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_i R_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-i}^2 \end{cases} \quad \text{...(2)}$$

Where

- p and q are orders of GARCH and ARCH respectively which are actually the number of lags.
- ε_t is the error term which is assumed to be normally distributed with mean zero and conditional variance σ_t^2.
- Returns are represented by Y_t and their mean value μ is positive and small.
- The model parameters are represented by α_0, α_i *and* β_j and they are also relative weights of the lagged terms and usually assumed to be non-negative.

Estimation of parameters with the GARCH approach requires the use of Maximum Likelihood Estimation (MLE) method.

In this paper conditional variance (Volatility) can be estimated using the GARCH (1, 1) Model which is given by

$$\begin{cases} Y_t = \mu + \sigma_t \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 R_{t-1}^2 + \beta_j \sigma_{t-1}^2 \end{cases} \quad \text{...(3)}$$

Where R_{t-1}^2 *and* σ_{t-1}^2 squared residuals and conditional variance of the previous day. The residuals of a return at time t may be given as $Y_t - \mu = \sigma_t \varepsilon_t \Rightarrow R_t = \sigma_t \varepsilon_t$

Methodology cont

To obtain the volatility of the returns, it is derived as follows;

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

But $\alpha_0 = \gamma V_L$ where γ is a weight assigned to the long run average variance rate V_L.

Since weights must sum upto 1

$$\gamma + \alpha_1 + \beta_1 = 1 \Rightarrow \gamma = 1 - \alpha_1 - \beta_1$$

This implies that

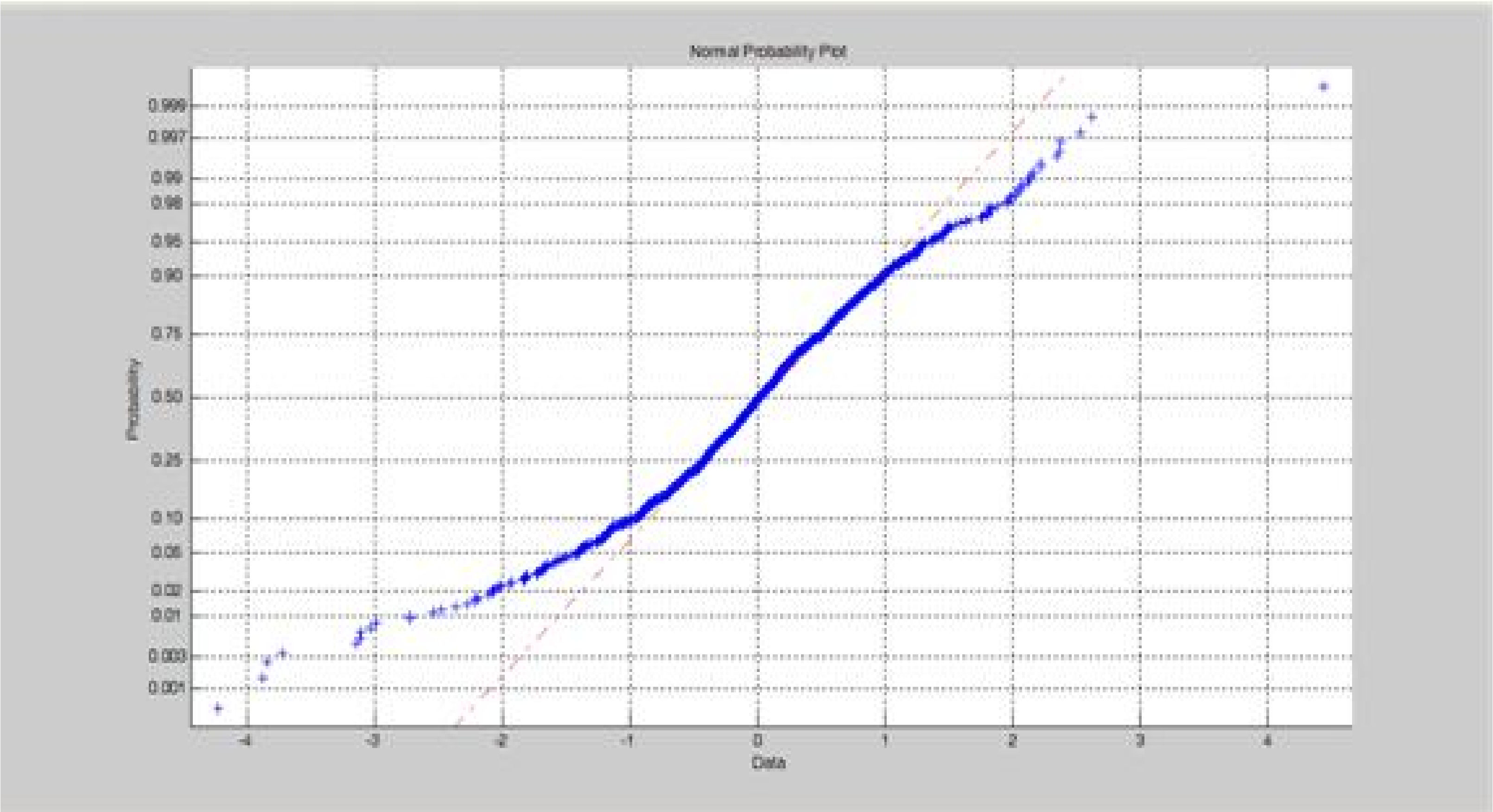
$$V_L = \frac{\alpha_0}{1 - \alpha_1 - \beta_1} \quad \text{.......................................(4)}$$

This means that as the lag increases the variance forecast converges to unconditional variance given by equation (4).

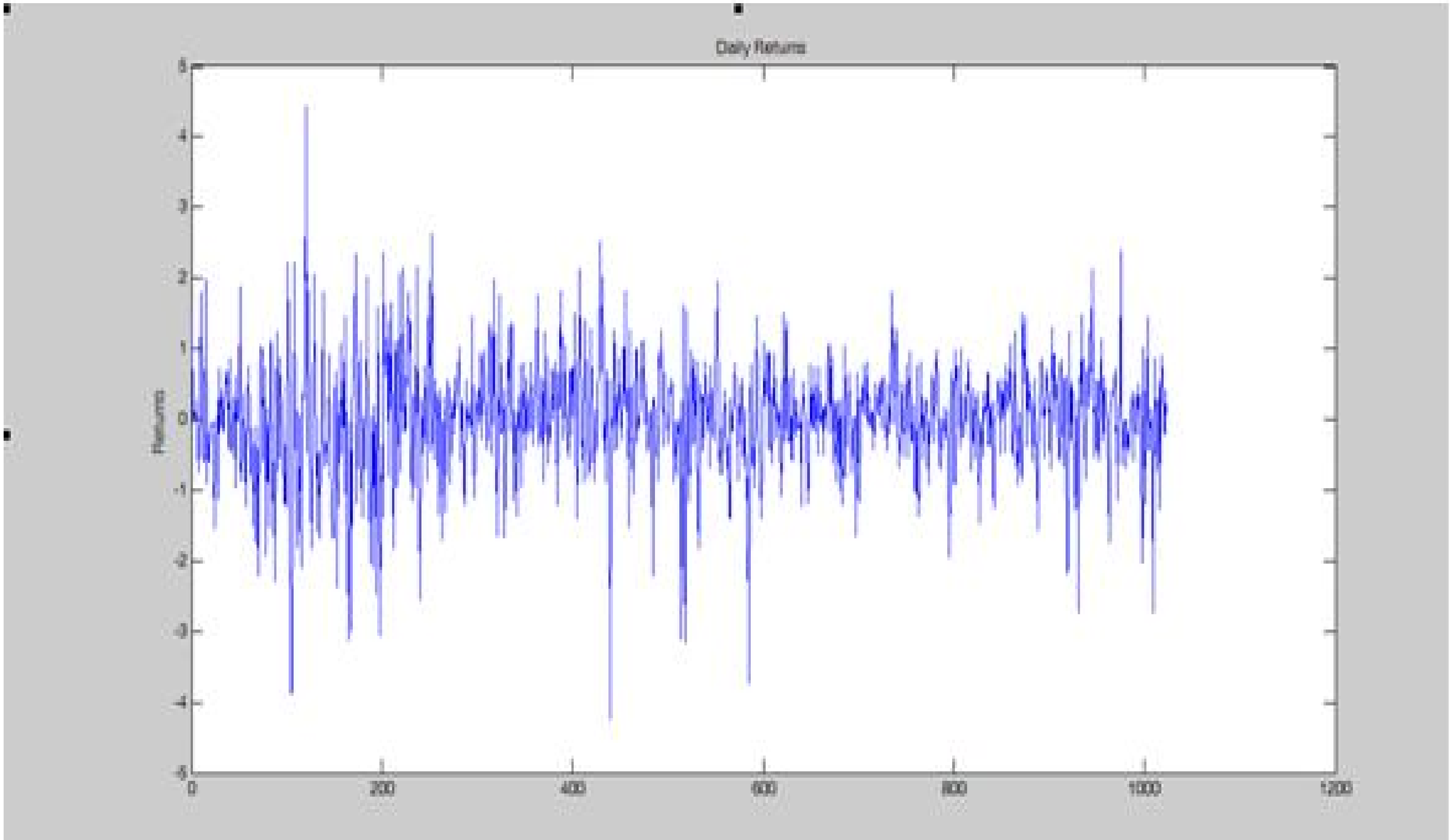
RESULTS AND DISCUSSION

- In order to predict the volatility of a time series data, GARCH model is fitted to the Time series data. This is achieved through the estimation of parameters by the Maximum Likelihood Estimation (MLE). During the estimation of unknown parameters, estimation of standard deviation series are calculated recursively using equation (3).
- Most financial time series data are associated with fat tailness and volatility clustering which the GARCH models accounts for. Excess Kurtosis can be observed from the probability distributions of assets returns which actually exhibit fatter tails than the Gaussian distribution.

EXCESS KURTOSIS



VOLATILITY CLUSTERING



- Volatility clustering or persistence indicates a serial dependence in the time series data.
- GARCH models applies the general understanding of volatility dependence to estimate the impacts of previous forecast error and volatility in obtaining the current volatility.
- This volatility clustering (suggesting changing variance) accounts for excess kurtosis observed in financial data.
- Volatility clustering is the effect that GARCH is designed to measure.

AUTOCORELATION FUNCTION

Table 1: Ljung –Box – Pierce Q – test

H	P Value	Test statistic	Critical Value
1.0000	0.2226	44.9440	18.3070
1.0000	0.6160	51.7722	24.9958
1.0000	0.5282	60.8362	31.4104

ESTIMATION OF GARCH PARAMETERS

The estimated parameters and their corresponding standard errors can be observed in table 2 below.

Table 2: Estimated Parameters

Parameter	**Value**	**Standard Error**	**T Statistic**
c	0.020418	0.026446	0.7721
k	0.011819	0.0050396	2.3453
GARCH(1)	0.94404	0.012951	72.8932
ARCH(1)	0.040308	0.0079053	5.0989

From Table 2, the conditional mean and the conditional variance (Volatility) model that best fits the observed data is

$Y_t = 0.020418 + \varepsilon_t$ and

$$\sigma_t^2 = 0.011819 + 0.94404\sigma_{t-1}^2 + 0.040308\varepsilon_{t-1}^2$$

From table 2, it can be observed that most of the information are from the previous days forecast amounting to about 94% and there is a minimal change on the arrival of new information and there is a very small effect on the long run average variance.The long run average variance per day implied by the model is given by equation (4).

That is $V_L = \frac{0.011819}{1-0.040308-0.94404} = \frac{0.011819}{0.015652} = 0.7551$

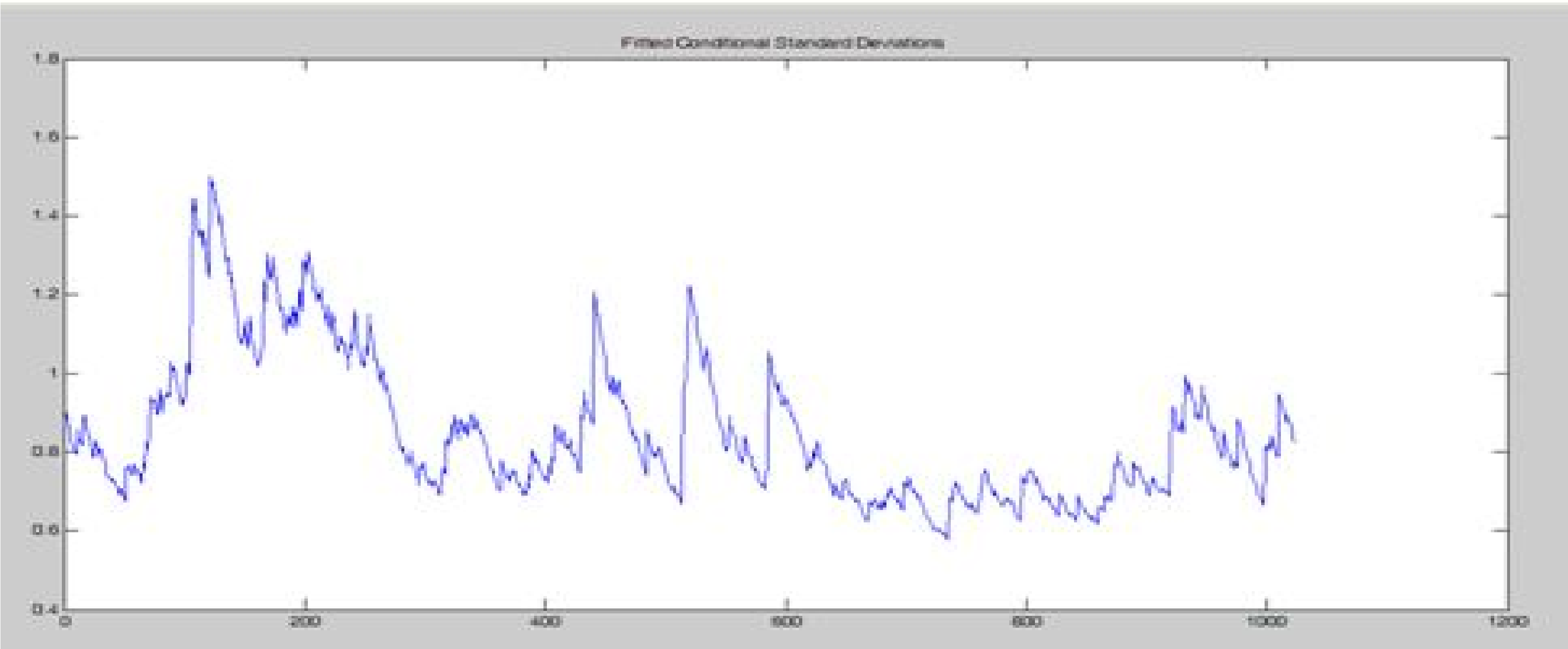
Thus the corresponding volatility is given by $\sqrt{0.755111167} = 0.86897$.

This means that Volatility is 86.897% per day.

PLOTTING VOLATILITIES

This means that as the number of horizons is increased to infinity the conditi
volatility approaches the asymptotic value 0.86897.

Table 3 shows conditional volatilities derived from the fitted retur
equity prices. This also shows that the assumption of independence and ident
distribution (iid) is not realistic since financial returns tend to occur in cluste
clustering).



CONCLUSION

- From the results it can be observed that equities of Barclays Bank of Kenya are highly volatile. This can be observed in the fact that volatility is approximately 87% which confirm the fact that stocks have high risk return on investments.
- It can also be concluded that strong GARCH effects can be observed in this financial market.