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# Estimation of Risk in Rwanda Exchange Rate

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**Abstract:** ***Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach was applied to Rwanda Exchange rate returns to estimating current volatility. We fitted autoregressive (AR) model with GARCH errors to the daily exchange rate returns using Quasi-Maximum Likelihood Estimation (Q-MLE) method to get the current volatility and asymptotic properties of the estimators were given. The appropriate GARCH model for each currency was selected using Akaike Information Criterion (AIC). Jarque Bera test for normality was applied and showed that both returns and residuals have fat tails behaviour. Lagrange Multiplier test showed ARCH effects presence in residuals. Results were used to estimate risk in the Rwanda exchange rate process.***

**Keywords:** Exchange rate, Estimation, GARCH model, risk and Volatility

## 1. Introduction

Exchange rates are a challenging concept despite the fact that one has to deal with foreign exchange rates whenever he/she travels to foreign country. Exchange rates markets are world decentralized marketplaces that determine the relative values of different currencies. Risk is a random variable transforming unforeseen future states of the world into values representing profits and losses. It is a common phenomenon in all areas of finance. The risk in foreign exchange can be defined as exposure to uncertainty and it cannot be dismissed in exchange markets since both importers and exporters of goods and services are affected by exchange rates fluctuations. Exchange rate risk (also known as Foreign exchange risk or currency risk) refers to a financial risk posed by an exposure to unanticipated changes in the exchange rate between two currencies. It may also be defined as the variability of a portfolio's value caused by uncertain fluctuations in the exchange rates. According to Madura (1989) exchange rate risk is related to the effect of unexpected exchange rate changes on the value of the firm. A value of any currency fluctuates as its demand and supply fluctuates, this means that if demand decrease or supply increase this can cause depreciation of the currency's value. On other hand if supply decrease and demand increase this can cause appreciation of the value of currency.

The modern era of risk measurement and estimation for exchange rate positions started in 1973. The risk managers and investors became concerned about the impact of exchange rate fluctuations on portfolios. Thereafter, exchange rates are among the most watched analyzed and governmentally manipulated economic measures. Exchange rate fluctuations have become an essential subject macroeconomic analysis and have received a great deal of interest from academics, financial economists and policymakers, particularly after the collapse of the Bretton Woods agreement of fixed exchange rates among major industries countries.

There are three main types of exchange rate risk (i) *Transaction risk (*cash flow risk and deals with the effect of exchange rate). (ii) *Translation risk* (balance sheet exchange rate risk). (iii) *Economic risk (*reflects the risk to the firm's present value of future operating cash flows from exchange rate movements). To deal with the exchange rate risk, a firm needs to determine the specific type of currency risk exposure, factors influence exchange rate and also to find out a suitable technique for estimating it. In this study; we are dealing with exchange rate returns. In exchange rates, we are concerned with the estimation of extreme risk due to the exchange rates fluctuations.

In the past years, many techniques of estimating value at risk have been developed, but those that seem to be the most successful and popular are: Generalized Autoregressive Conditional Heteroskedasticity models and extreme value theory approach. Empirical evidence found that financial return series such as exchange rate returns exhibit certain stylized facts such as volatility clustering, heavy-tailedness, heteroskedasticity and non-linearity. The GARCH family models proposed by Bollerslev (1986) was introduced to deal with these problems of patterns facts in financial data. These models manage changing volatility with the assumption of conditional normality. In this work we applied GARCH model to estimate exchange rate volatility of Rwanda Francs (Frw) versus Kenya Shillings, US Dollars, Euro and Sterling Pound respectively for the time period between 1st January 2002 and 31st December 2012.

## 2. Literature Review

Risk is related to undesirable outcome, but volatility can be defined as a measurement of the change in price over a given period of time and is normally measured with volatility. Volatility is related to risk but not exactly the same. Exchange rate volatility is a measure of the fluctuations in an exchange rate. When volatility in exchange rate increases this lead to uncertainty in pricing and this hurts importers who spend more for the same quantity incase of local currency depreciation and exporters benefit from this depreciation of local currency, Smith et al ( 1990).

Maana et al (2010) estimated exchange rate volatility of Kenya exchange rate using GARCH (1,1) model. They found that the importers and exporters of goods and services are both affected by exchange rate fluctuations and they have agreed with Smith et al(1990) that the volatility has significances on the profits and survival of business enterprises.

A considerable amount of research in last years, including; Andersen (1996), Ghysels (1996) estimated the volatility as non-constant and non-symmetric with left fat tail. Some argued that the true volatility cannot be estimated because there is no relationship between prior, current, and future volatilities for financial assets. According to Peter et al (2002), the foreign exchange rates can be subject to considerable daily fluctuations (up to 5 percent within one day), this can cause serious losses on open overnight positions. They quantified the risk by focusing on the tails of the distribution and showed how to use estimations to compute limits that a risk manager can set to open positions to avoid unexpected huge losses.

Researchers in the past years have found out two fundamental attributes regarding distributions of returns of financial assets returns. First, they found that most of the times the distributions of financial assets returns are not normal, for example see, Hull and White (1998). In 2001, Manganelli and Engle showed that financial returns, especially exchange rate and interest rate returns are not normally distributed, but fat-tailed, leptokurtic and skewed, suffer from volatility clustering and are not independent. Some researchers argue that the distribution should have fat tails, Longin (1996) and Neftci (2000), and others argue that it should not be symmetric, Glosten (1993).

Second attribute, some researchers found that the distributions of financial assets returns are not constant over time. Such findings are related to another field of research in finance: the prediction of volatility of financial assets. There have been a lot of debate about the attributes of volatility; whether the volatility is time-varying or constant, whether it should be weighted through time or not, or what time interval from past is relevant for current volatility, Nelson (1991).

## 3. Methodology

The purpose of this study was to estimate risk in Rwanda exchange rate returns. The empirical analysis has been done using opening daily exchange rates for the following currencies pairs: Frw/Ksh, Frw/USD, Frw/Euro and Frw/Pound refer to the Rwanda Francs against Kenya Shillings, US Dollars, Euros and Sterling Pounds respectively. The choice of Sterling pounds, Euros and US Dollars was based on their relative proportions in the Bank's foreign exchange investment portfolio. The choice of Kenya Shillings was based on its strength in the EAST Africa currencies. In each selected currency we based also on its currency composition of imports. The data used were the **2758** daily observations of average of buying and selling of the Rwanda Exchange Rate covering the period from January 1st 2002 to December 31st 2012. The daily data were obtained from National Bank of Rwanda. We have defined the following models;

$$r_t = log\left(\frac{EX_{t-1}}{EX_t}\right), t = 1,2,\dots,T \qquad (3.1)$$

Where $r_t$ represents the daily returns to the exchange rate at time $t \in T$ where $T$ is the total number of observations. $EX_t$ and $EX_{t-1}$ denote the exchange rate at the current day and that of previous day respectively.

Exchange rate returns can also be modeled as Autoregressive model with conditionally heteroskedastic financial time series as follows:

$$r_t = \mu(y_t, z_t) + \sigma(y_t, z_t)e_t, t = 1,2,\dots,T \qquad (3.2)$$

$y_t = (r_{t-1}, \dots, r_{t-\pi})$,Where $y_t$ represents endogenous variables in the model, $z_t$ represents Explanatory variables consisting of information other than the past of the returns. $\mu$ represents conditional expected return which may be arbitrary, $\sigma$ represents conditional volatility of daily exchange rate returns, $\pi$ represents the order of Autoregressive, $e_t$ represents standardized returns. Many researchers have found that news has strong effects on foreign exchange volatility and a good model for financial returns should capture; the series correlationn, volatility-clustering, as well as fat tails behavior.

To deal with these two main characteristics about financial returns, Bollerslev (1986) generalized ARCH model by adding the concept that the volatility for tomorrow depends not only on the past realizations but it depends too on the errors of the volatility predicted and came up with GARCH model. The general framework of GARCH $(p,q)$ is represented by allowing the current conditional variance to depend on the first $p$ past Conditional variance as well as the $q$ past squared innovations. Now let us assume that returns follow normal distribution and can be redefined as

$$r_t = \sigma_t e_t, \epsilon_t \sim (0, \sigma_t^2) \qquad (3.3)$$

Where

$$\sigma_t = \sqrt{\omega + \sum_{i=1}^{q} \alpha_i r_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2}$$

which is a GARCH $(p,q)$ process. Where $q \geq 0$ is the number of lagged of squared residuals terms and $p \geq 0$ is the number of lagged of variance terms. The sizes of the parameters $\alpha_i$ and $\beta_j$ determine the short run dynamics of the resulting volatility process. The non-negativity of $\alpha_i$ and $\beta_j$ ensure that $\sigma_t^2$ is strictly positive. The innovation $e_t$ is an independently and identically distributed process with zero mean and unity variance. The strict stationarity is ensured by $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$.

Large ARCH error coefficients $\alpha_i$ imply that volatility reacts significantly to market movements. Large GARCH coefficients $\beta_j$ indicate that shocks to the conditional variance take long time to die out. High $\alpha_i$ coefficients, relative to $\beta_j$ indicate that volatility tends to be more extreme. Since $\sigma_t^2$ is the one-period ahead forecast volatility based on the past information, it is called conditional volatility and it is specified as a function of three terms: unconditional volatility $\omega$, news about volatility from the previous period measured as the lag of the squared residuals from the mean equation $r_{t-1}^2$ (ARCH term) and last period volatility $\sigma_{t-1}^2$ (GARCH term).

We therefore estimated volatility $\sigma_t$ as follows.

$$\hat{\sigma}_t = \sqrt{\widehat{\omega} + \sum_{i=1}^{q} \hat{\alpha}_i\, r_{t-i}^2 + \sum_{j=1}^{p} \hat{\beta}_j\, \sigma_{t-j}^2} \tag{3.4}$$

# 4. Results

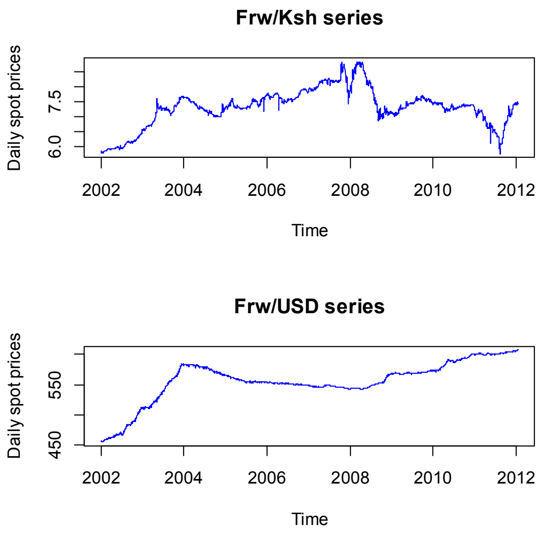


**Figure 1:** Trends in Frw vs Ksh and Frw/ USD

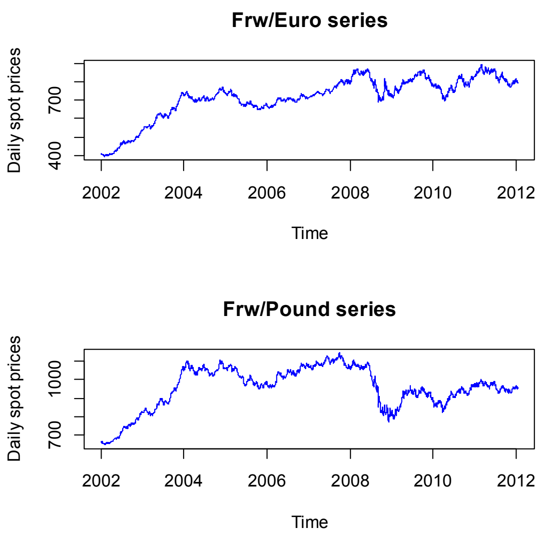


**Figure 2:** Trends in Frw vs Euros and Pounds

The Frw/EUR and Frw/GBP refer to the Rwanda francs against Euros and Rwanda francs versus Sterling Pound respectively. The Plots in Figures 1and 2 reveal general trends with high uncertainty in the exchange rates for all currencies between the end of 2003 and the beginning of 2004, and relative stability thereafter. The year 2003, financial year showed a depreciation of the Rwanda francs against foreign currencies. The Rwanda francs (Frw) depreciated by 13.36% against the USD, 36% against the Euro, 25.5% against British Pound and also 15.73% against Shillings. This high depreciation is due to the supplying of banknotes and coins, the issue of new banknotes and the distribution of notes unfit for circulation with a view to ensuring sound management of money in circulation. The expenses associated with the end of political transitional period and the current external deficit deteriorated also contributing sharply to the depreciation of Rwandan franc against foreign currencies in that period. With regard to principal missions, the National Bank of Rwanda (BNR) ensured better monetary policy implementation with a view to preserving the value of the National currency and ensuring its stability. It implemented a prudent monetary policy which was adapted to the economic conditions of the time, so as to support the Government's economic policy.

In the field of exchange, the BNR organized and managed carefully the exchange market by spelling out clearly the conditions governing exchange operations in order to maintain the external stability of the Francs.

As it can be seen in Table1, the daily exchange rate series has a significant difference between its maximum and minimum specifically, in Rwanda Francs against Euros (Frw/Euro) as well as Francs versus Sterling pound (Frw/Pound). The standard deviation of Frw/Euro series is 13.79% of its mean and that of Frw/Pound series is 11.56% of its mean. But the Rwanda Francs against Kenya Shilling (Frw/Ksh) exhibits low difference as well as Francs versus US Dollars (Frw/USD). The standard deviation of Frw/Ksh series is 8,20% of its mean and that of Frw/USD is insignificant 6.47% of its mean.

**Table 1:** Basic statistics of Exchange rate series

| *Statistics* | *Ksh* | *USD* | *Euro* | *Pound* |
|---|---|---|---|---|
| Mean | 7.317 | 560.2 | 799.7 | 956.9 |
| Median | 7.378 | 560.1 | 719.7 | 967.1 |
| St.dev | 0.6027037 | 36.25195 | 110.3008 | 110.6573 |
| Maximum | 8.829 | 631.5 | 893.5 | 1147.0 |
| Minimum | 5.759 | 455.5 | 394.9 | 645.6 |
| Observations | 2758 | 2758 | 2758 | 2758 |

## 4.1 Daily Exchange Rate Returns

In order to estimate the volatility in the exchange rates, we used logarithm rates returns. The log-returns in plots in Figures 3 and 4 show that the data appear to be stationary in mean after logarithm transformation. These plots also reveal dependence structure where period of high returns tend to be followed by the high returns as well as the period of low returns tend to be followed by low returns. This is evidence of short-range dependence (volatility clustering in data), which must cast doubt on the assumption of independent and identically distributed $i.i.d$ of data. The clustering of exchange rate returns data indicates presence of stochastic volatility in exchange rate series. These Plots allow identifying the most extreme losses and their approximate time occurrence.

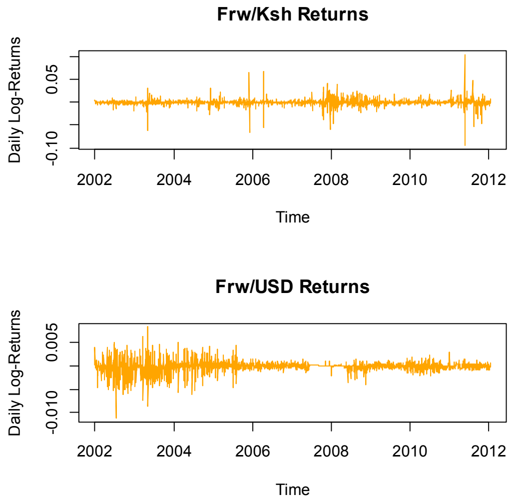


**Figure 3:** Daily Returns Frw vs Shs and USD

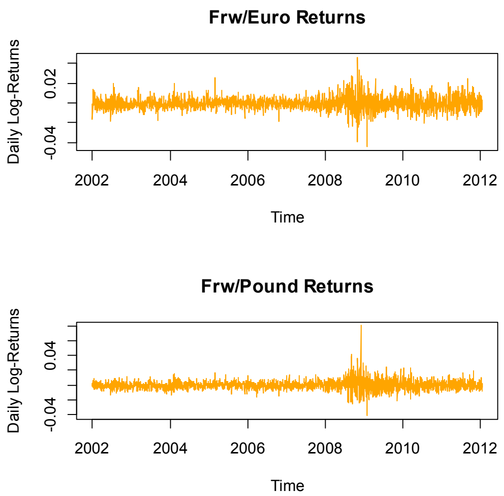


**Figure 4:** Daily Returns Frw/Euro and Frw/ Pound

The distributions of returns in Frw/Ksh and in Frw/USD exhibit negative skewness (means frequent small gains and few extreme losses) to indicating that they have what statisticians call a long left tail. For investors can mean a greater change of extremely negative outcomes. The returns series of Frw/Euro and that of Frw/Pound have positive skewnss coefficients which indicate that the distributions of the returns in both currencies are slightly right skewed. These imply that depreciations in the exchange rates occur slightly more often than appreciation. This indicates that for investors, can have frequent small negative outcomes and few extreme gains. The descriptive statistics of returns are presented in Tab2 below.

**Table 2:** Summary statistics of Log-Returns data

| Statistics | Frw/Ksh | Frw/USD | Frw/Euro | Frw/Pound |
|---|---|---|---|---|
| Mean | -8.905e-05 | -.00011649 | -.00026462 | -0.0001570 |
| Median | -4.329e-05 | 0.0000000 | -0.0003855 | -0.0001134 |
| Minimum | -0.0953246 | -0.0111935 | -.04449859 | -0.0413000 |
| Maximum | 0.1048363 | 0.00833903 | 0.04643833 | 0.0808800 |
| S.dev | 0.00670291 | 0.0011167 | 0.00616065 | 0.006094035 |
| Skewness | -0.1100568 | -1.065407 | 0.2640723 | 1.15312 |
| Kurtosis | 60.08347 | 12.5501 | 4.642768 | 15.3189 |
| JB.Test (p-value) | <2.2e-16 | < 2.2e-16 | < 2.2e-16 | < 2.2e-16 |
| ADF. Stats (14) | -12.5243 | -9.2241 | -12.02 | -11.9874 |
| ADF.Test (p-value) | 0.01 | 0.01 | 0.01 | 0.01 |
| Significance level | 0.05 | 0.05 | 0.05 | 0.05 |
| No.of obs | 2758 | 2758 | 2758 | 2758 |

The kurtosis coefficients for log-returns of all currencies are much greater than three (>3) for normal distribution. This indicates that the underlying distributions of exchange rate returns have fat tails. Jarque Bera test for normality rejects null hypothesis since $p - value$ is too small number compare to 5% confidence level for all the currencies. This indicates that the distribution of exchange rate returns for all the currencies have tails which are significantly heavier than that of normal distribution. Augmented Dickey Fuller (ADF) test used to test for stationality revealed that returns for all currencies are stationary in mean. The ADF statistics used in the test is a negative number for all the currencies. The negative sign indicates the degree of null hypothesis rejection where the more negative indicates the stronger rejection of the null hypothesis.

Akaike and Bayesian information criterions for best model selection reveal that GARCH (1,3) is the best for Frw/Ksh, GARCH(1,2) for Frw/USD and GARCH(1,1) is the best model for both Frw/Euro and Frw/Pound.

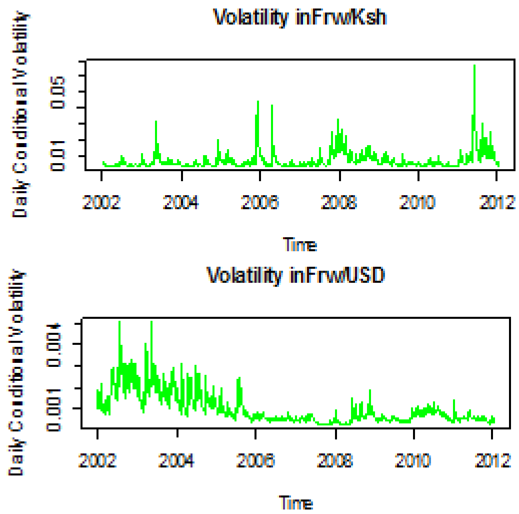


**Figure 5:** Daily Volatility for Frw/Ksh and Frw/USD

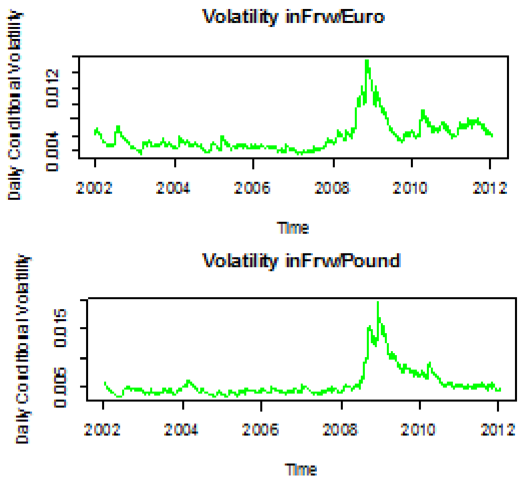


**Figure 6:** Daily Volatility for Frw/Euro and Frw/GBP

In all GARCH models the estimated parameters are significant at 5% level. As can be seen in Table3 below, Jarque Bera (J.B) test for residuals showed that p-value is less than 5% confidence level therefore the null hypothesis was rejected to indicate that residuals of returns series are not normally distributed. Lagrange Multiplier (LM) test for ARCH effects rejects the null hypothesis of no ARCH effects at 12 degrees of freedom for all currencies. This indicates the presence of ARCH effects in residuals of exchange rate returns. The ARCH effects continue to decrease with the increase of the number of lags. The ARCH effects in the exchange rate returns of Frw/Ksh dies out after (678) lags. The presence of ARCH effects in the returns of Frw/USD dies out after (916), which of the returns of Frw/Euro dies out after (906) and in Frw/Pound it dies out after (645) lags.

**Table 3:** Summary Statistics of CARCH innovations

| *Tests* | *statistics* | *Ksh* | *USD* | *Euro* | *Pound* |
|---|---|---|---|---|---|
| J.B | $\chi^2(2)$ | 415489.8 | 18654.85 | 2515.073 | 27626.04 |
| | $p.value$ | <2.2e-16 | <2.2e-16 | <2.2e-16 | <2.2e-16 |
| LM | $\chi^2(12)$ | 528.3464 | 323.4492 | 376.3599 | 191.2635 |
| | $p.value$ | 2.2e-16 | 2.2e-16 | 2.2e-16 | 2.2e-16 |
| ADF | $\chi^2(14)$ | -12.5243 | -9.2241 | -12.02 | -11.9874 |
| | $p.value$ | 0.01 | 0.01 | 0.01 | 0.01 |

The results can be summarized as follow, neither the exchange rate returns series or the residuals series can be considered to be normally distributed since both the series have a leptokurtic distributions. This indicates that the curvatures are high in the middle of the distributions and tails are fatter than normal distribution. These mean that even if we assumed that $e_t$ is independent and identically distributed standard normal we still get returns have kurtosis great than 3. Therefore, we can conclude that the assumption of conditional normality is not realistic for real data.

## 5. Conclusion and Recommendation

This study estimated risk in Rwanda exchange rate series using GARCH model. The data used were daily exchange rate series for the period from January 2002 to December 2012. Quasi-Maximum Likelihood estimation method applied has parametric estimators that are consistent and asymptotically normal. Jarque Bera test used for normality testing showed that exchange rate data are non-normal and exhibit leptokurtosis and positive skewness. Lagrange Multiplier test for ARCH effects revealed presence of ARCH effects in both returns series and residuals. Augmented Dickey Fuller test for unity root showed that the return series for all currencies are stationary in mean. Results of this work will contribute a lot to understanding of how changes in exchange rate affect the prices of goods and services in international trade.

Nelson (1991) introduced Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model and listed some shortcomings of the GARCH models. First, the lack of symmetry in the response of shocks, Secondly, the GARCH models impose parameter restrictions to ensure positive of the conditional variance and finally he showed that for the GARCH models to measure the persistence is very difficult. Now from these drawbacks listed by Nelson we recommend to future research to use asymmetry model to see whether these shortcoming can have significance impact to risk estimation.

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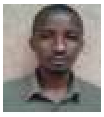

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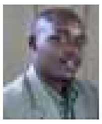

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