

Modeling Asymmetric Effect in African Currency Markets: Evidence from Kenya

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Abstract

Volatility modeling has of recent received considerable attention in the literature. The US-induced global financial crisis offers more reasons to explore the volatility structures of currency markets. The present study seeks to examine empirically the possibility of asymmetry in Kenyan exchange rate volatility in the light of the global financial crisis of 2008-09 and the election violence of January-February 2008. GARCH and EGARCH models involving GED specification were employed. Though specification tests favoured GARCH, EGARCH estimation suggested the possibility of asymmetry in Kenyan shillings. In addition, the estimated effect of the crises on returns and conditional volatility are about .04% and $2.19 \times 10^{-4}\%$, respectively. Further, the estimated values of the ARCH and GARCH effects clearly indicated that the conditional volatility (on aggregate) reacted more intensely to shocks than to the market movements. The subsample comparisons showed that while the conditional volatility reacted more intensely to market movements (than to shocks) during the pre-crisis and election

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periods, it was more influenced by shocks in the global crisis period. Finally, the article recommends some measures that would help to restore exchange rate stability in the economy.

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1 Introduction

What is volatility? It is the extent to which return on an underlying asset fluctuates over a given period of time. Volatility models are therefore, statistical models used in measuring the volatility of the return of any given asset.

Why do asymmetries matter in financial markets? According to Engle [1], the presence of volatility clusters is a well-known characteristic of financial time series, but it does not fully explain the volatility dynamics of these series. Other features (such as asymmetries) ought to be considered in volatility models to provide better models and more accurate forecasts. When modeling volatility dynamics, it is important to investigate the existence or otherwise of asymmetric effect for a variety of reasons: Option pricing, it is known, rests on the correct modeling of the underlying asset. In particular, the most commonly used model for foreign exchange options is that of Garman and Kohlhagen [2] which assumes log-normality based on constant volatility, in clear contradiction with the existing evidence of heteroscedasticity. Even when non-constant volatility is identified in the form of volatility smiles (a long-observed pattern in which at-the-money options tend to have lower implied volatilities than other options), a misconception remains since leverage is (till now) best represented by volatility skews. Moreover, the representation of foreign exchange options pricing always assume a symmetric volatility smile (Hull [3]) leading to incorrect valuations.

Further, modeling asymmetry is crucial for market risk measures, that is, Value at Risk (VaR). This is a widely used measure of market risk mandatory for financial institutions in countries that have adopted the Basilea agreement. Now, VaR focuses on the left tail of the return distribution and computes the worst probable loss within a certain level of confidence. Ignoring asymmetry may result in underestimating that risk (Engle [1]).

What then is asymmetric volatility? Volatility is asymmetric when appreciation (depreciation) of the domestic currency relative to the foreign currency tends to induce a higher increase in volatility of the domestic currency than a depreciation (appreciation) of the same magnitude in the subsequent period (Kahya, *et al.* [4]; and Kocenda and Valachy [5]).

Up till the early nineties, the consensus in the currency market is that there is no asymmetric volatility in foreign exchange (FOREX, hereafter). Bollerslev *et al.* [6], for instance, wrote: “[W]hereas stock returns have been found to exhibit some degree of asymmetry in their conditional variances, the two-sided nature of the foreign exchange market makes such asymmetries less likely.” Later, empirical evidences emerged to support the existence of asymmetric effect in same: Byers and Peel [7] documented evidence of asymmetric volatility in European exchange rates during 1922-1925, Tse and Tsui [8] in Malaysian ringgit, McKenzie [9] in Australian dollar, and Adler and Qi [10] in Mexican peso, all against US dollar.

Studies on asymmetric volatility have been limited to the stock market. In general, empirical studies on asymmetric behavior for FOREX market are relatively few. For African currency market, they are very few. Moreover, the very few existing ones did not capture the asymmetries which may exist in the conditional volatility, notable exceptions being Olowe [11], Bouoiyour and Selmi [12] and Okyere *et al.* [13].

Further, result on asymmetric volatility in African FOREX market is at best mixed: While Olowe [11] reported “no asymmetric volatility” in the Nigerian foreign exchange market, Bouoiyour and Selmi [12] and Okyere *et al.* [13] found

evidence of asymmetry in the Egyptian pound and Ghanaian cedi, respectively. Recently, Ntwiga [14] analyzed the effect of election violence on Kenyan FOREX volatility. Though the study did not consider asymmetry, it however succeeded in showing that Kenyan exchange rates could be modeled using volatility models. More to the point, the study employed GARCH model which, according to Nelson [15], is in itself a restrictive model, in the sense that it assumes that only the magnitude and not the positivity or negativity of unanticipated excess returns determines features of the conditional variance. And as such is not appropriate to model asymmetry in volatility in the context of the stated definition in the third paragraph. Thus to our knowledge, the possibility of asymmetric volatility is yet to be investigated in the Kenyan currency market and also, the asymmetry associated with African FOREX market, in general, has not been fully examined. Consequently, the conclusion from this study would have far-reaching implications on African economies, and particularly, an agro-based economy like Kenya, whose economic system depends largely on export commodities like tea, horticulture and coffee (Mwega [16]).

The main objective of the present study is to examine empirically the possibility of asymmetry in Kenyan exchange rate volatility in the light of the recent global financial crisis. The US-originating financial crisis that recently engulfed the world economy offers more reasons to explore the possible asymmetric behavior in the exchange rates of developing countries. The belief is that countries in sub-Saharan Africa are barely integrated into the global financial system, and consequently, would be spared the effects of the global financial crisis. However, results from different surveys have proven otherwise. Ben Ltaifa *et. al.* [17] for example, in a research on the impact of the crisis on the currencies of sub-Saharan Africa (SSA), reported that the currencies of many Sub-Saharan African countries suffered large depreciations with the onset of the global financial crisis. These large depreciations the study attributed to collapsing trade and financial flows which further led to substantial balance of payments gaps,

triggering fast depreciations and higher exchange rate volatility.

Kenya (being part of SSA) was not spared: The current account deficit rose from \$2.12 billion in 2008 to \$2.388 billion in the year, affecting the exchange rate and foreign exchange reserves. Implementation of the 2008/09 budget also faced numerous challenges, which included inability to achieve revenue targets and additional drought-related expenditures (Mwega [16]). There are several other country-specific studies on the impact of the crisis to African countries. See for example, Kilonzo [18], Anyanwu [19], among others.

The election violence of 2008 is another major crisis which makes the case of Kenya a peculiar one, worthy of investigation. It is of interest to determine the individual impact of the election violence and the global crisis on both exchange rate returns and volatility. This will provide information about the state of Kenyan capital market with a view to enhancing the economy viz-a-viz the Millenium Development Goals.

Another contribution of the present study is that two methods have been employed; the (i) dichotomous volatility models and (ii) standard statistical analysis of subsamples comparisons. Usually, for studies of this nature, the common approach is the latter, i.e. to divide the entire sample period into subperiods – pre-crises, during crises and post-crises. Then, obtain volatility equations based on the subsamples and compare the results. However, the present study acknowledges that this common approach is rather a mechanical estimation of the volatility model. Such a model may well have different parameters from year to year, and volatility may be triggered by changes in level (i.e. persistent movements in the same direction), in which case the interpretation would be rather different. Thus, it is important to investigate, first, if the change in conditional variance is as a result of the crises. In the light of this, the present paper introduces a dummy variable C in the volatility equation which takes value 1 during the crises period and 0 in the non-crises period. Once it has been established that the

crises have some impact then the second step is to investigate the extent using volatility equations obtained for subperiods.

The remainder of the paper is organized in the following manner. Section 2 reviews related literature. Section 3 describes developments in the Kenyan foreign exchange market before and during the crisis. Section 4 presents the data and the methodology. Section 5 discusses the results of the empirical tests. Finally, Section 6 contains the conclusion and recommendations.

2 Literature Review

This literature section can be separated in two (but not really distinct) parts. The first one discusses empirical results on asymmetric volatility in FOREX market with emphasis on Africa. The second one analyzes the recent crisis with respect to its effect on fluctuations in exchange rate.

2.1 Asymmetric Volatility in Exchange Rate Market

Wang and Yang [20] identified central bank intervention as one of the major causes of asymmetric volatility in foreign exchange market: As central banks intervene on one side of the market but not the other, interventions may lead to an asymmetric behavior in exchange rate volatility. Another cause is contrarian and herding investors: In the case of stock markets, Avramov *et al.* [21] reported that herding trades increase volatility as prices decline while contrarian trades reduce volatility following price increases. Now, Gencay, *et al.* [22] and Carpenter and Wang [23] have shown that contrarian trading and herding are present in the foreign exchange markets, thus, one would also expect asymmetric volatility.

Asymmetry in FOREX volatility has been studied extensively for developed markets (Wang and Yang [20]). However, it is well known that returns from

emerging financial markets have several features that distinguish them from developed markets. There are at least four distinguishing features of emerging market returns: higher sample average returns, low correlations with developed market returns, more predictable returns, and higher volatility (Bekaert and Wu [24]). These differences may have important implications for decision making by investors and policy makers. Hence, the later part of this section is dedicated to empirical results on asymmetry behavior in the African FOREX markets.

Olowe [11] found no evidence of asymmetry in the Nigerian currency market. The study investigated the volatility of Naira/Dollar exchange rates using a wide range of asymmetric GARCH models, namely, GARCH (1,1), GJR-GARCH(1,1), EGARCH(1,1), APARCH(1,1), IGARCH(1,1) and TS-GARCH(1,1) models. Using monthly data over the period January 1970 to December 2007, it rejected the hypothesis that asymmetric effect is present in Nigerian FOREX market. This is in sharp contrast to earlier studies in the developed economies.

In contrast, Bouoiyour and Selmi [12] documented the existence of asymmetric effect in Egyptian pound. The paper studied FOREX volatility using five different specifications of GARCH, namely, GARCH, EGARCH, GJR-GARCH, NGARCH and TGARCH. There were two main findings; first, specification tests (Akaike and Schwartz Information Criteria) identified EGARCH as the best fit for Egyptian currency, second, asymmetric effect was present in the Egyptian exchange rate market with positive shock increasing volatility more than the negative of the same magnitude.

Very recently, Okyere *et. al.* [13] also using GARCH, EGARCH and TARCH to model asymmetries in Ghanaian cedi/US dollar submitted that positive shock implied a higher next period conditional variance.

To our knowledge, we have no empirical evidence to rely on for most of the African countries, except for the ones mentioned above. These empirical studies present mixed results on asymmetric volatility in African exchange rate market though bulk of the evidence indicates the presence of asymmetry in volatility.

Moreover, the case of Kenya, in particular, is yet to be investigated. Given the peculiarity in each financial market, it is important to examine the consistency of Kenyan Shillings in the context of the above-mentioned stylized facts.

2.2 Exchange Rate Volatility and Financial Crises

The purpose of this section is to give an overview of literature on exchange rate volatility and financial crises. More detailed descriptions of the recent crisis can be found in Ben Ltaifa *et. al.* [17] and Melvin and Taylor [25], among others. Interested reader is also invited to see Forbes and Rigobon [26] and Glick and Rose [27] for theories on crises and contagion.

That financial shocks affect exchange rate volatility is well documented in the empirical literature. But we shall review some recent studies.

Baharumshah and Hooi [28] using EGARCH model reported strong evidence of asymmetry before and after the Asian crisis for most of the currencies (the Korean won, the Philippine peso, the Thai baht, the Malaysian ringgit and the Singapore dollar) that were considered. Oga and Polasek [29] did not consider asymmetry; however, it agreed with earlier studies that the Asian crisis caused volatility structure change in East Asian currencies.

Though quite a number of studies have examined the impact of the previous crises, particularly the Asian crisis, on exchange rate volatility, yet the recent crisis is worth investigating because, according to Kohler [30], it differs from the previous ones in a number of ways: First, the place of origin; and second, the scale of contagion. The Asian and the Argentinean episodes originated in emerging market economies; while in the most recent crisis the epicentre of the turmoil was the US banking system. Significant contagion was recorded in all the three episodes, in the Asian crisis it was largely confined to the region and that of the Argentinean episode was mainly confined to the neighboring countries, such as Brazil. The latest crisis, by contrast, was truly global.

At the onset of the crisis, there was no agreement (in the existing literature) as to whether African region would be spared the rippling effects of the crisis. Studies such as Horhota and Matei [31] anticipated very minimal (or no) effect, their reason being that the region is barely integrated into the global financial system. However, the International Monetary Fund (IMF) [32] argued that Low Income Countries (LICs) (such as Africa) will be exposed to the current global downturn now more than in previous episodes because they are more integrated than before with the world economy through trade, FDI, and remittances. We note that the latter argument agrees with the economic globalization index presented in Table 1 which shows that Africa has experienced a steady increase in economic globalization in the last four decades and consequently, is steadily integrating into the world markets.

For Kenya, the Ministry of Finance and CBK officials postulated that the impacts would be indirect and most likely small. According to CBK [33], “Kenya is primarily a rural agro-based economy with only a small minority of the population directly interfacing with the developed world. The main sectors likely to feel any significant impact [are] tourism and commercially-oriented agriculture such as horticulture, tea and coffee. Other effects might be felt through foreign exchange volatility, inputs (cost and availability) and also the credit and trade restrictions.

AfDB [34] identified two transmission channels of the crisis into Africa: trade flows and capital flows (such as foreign direct investment, private capital flows and remittances). For Kenyan economy in particular, Mwega [16] highlighted four key mechanisms of transmission which are similar to the transmission channels earlier listed: private capital flows, trade, remittances, and foreign aid.

There are very few empirical studies relating FOREX volatility to the recent financial crisis in the context of African economies. In what follows the paper highlights some of the differences in those studies.

First there is no agreement as to when the crisis started. Ben Ltaifa *et. al.* [17] defined the crisis period as June 2008 – March 2009. Coudert *et. al.* [35] selected the larger period July 2007, the time of the bursting of the subprime crisis, to September 2009. Later, Olowe [11] defined the crisis period as beginning from the time the takeover of Fannie Mae (Federal National Mortgage Association) and Freddie Mac (Federal Home Loan Mortgage Corporation) by the American government was officially made public and extending up to March 2009. In line with the chronology of the crisis in Kenya as documented in Kilonzo [18] and Ben Ltaifa *et. al.* [17], and also incorporating the presidential election violence, this paper defines the crises period for Kenya as January 2008 – March 2009.

Second, in difference with methods, Ben Ltaifa *et. al.* [17] measured exchange rate volatility as the ratio of the standard deviation of the exchange rate to its annual average; whereas it has been established that the traditional measure of volatility as represented by variance or standard deviation is unconditional and does not recognize that there are patterns in asset volatility e.g. time-varying and clustering properties. Coudert *et al.* [35] employed both the squared monthly returns of exchange rates (in logarithms) and GARCH model in measuring FOREX volatility of certain emerging economies. While the former method suffers the same drawback as standard deviation the latter is inadequate because the use of GARCH model is restrictive (Nelson [15]). And besides, if the presence of asymmetric volatility is not accounted for, it will lead to the underestimation of the Value at Risk (Engle [1]). Finally, Olowe [11] used both GARCH and GJR-GARCH. However, as noted earlier, the dichotomous-GARCH model which he applied could only ascertain the presence of the impact of the crisis but could not provide the in-depth analysis of what went down during the period. The subsample comparison which, in addition, is being applied here is important especially for Kenyan economy in order to identify the individual impact of the election violence and the global crisis.

Earlier empirical findings agreed that the crisis had effect on exchange rate

volatilities of emerging economies but to what extent? Did the crisis cause volatility to increase or not? What is the individual impact of the election crisis and the global financial crisis? To these questions the present study attempts to offer answers.

3 Developments in the Kenyan Foreign Exchange Market: Before and During–the–Crises Review

Since the collapse of the generalized fixed exchange rate regime and the adoption of a generalized floating system by the industrialized countries in 1973, African countries have experimented with various types of exchange rate arrangements, ranging from a peg to a single currency, weighted currency basket, managed floating, independently floating exchange rate system and monetary zone arrangements, such as the CFA Franc Zone and the Common Monetary Area (CMA) of Southern Africa. The experiences of various African countries with exchange rate arrangements and management have, therefore, been diverse and varied as these countries have sought to find an optimal and sustainable exchange rate regime.

For Kenya, the shift from a fixed to a flexible exchange rate regime has been gradual. According to Ndung'u [36], from independence to 1974, the exchange rate for Kenya shilling was pegged to US dollar, but after discrete devaluations the peg was changed to the Special Drawing Rights (SDR). SDR was later abandoned because it was considered inadequate to maintain competitiveness of the shilling since the weights used did not reflect her trade pattern, which is more diversified. A crawling peg exchange rate regime was adopted until 1990 when it was replaced with a dual exchange rate system. The new regime lasted until October 1993, when, after further devaluations, the official exchange rate was merged with the market rate and the shilling was allowed to float. Following the years after the

liberalization of the shilling, the exchange rate went through several phases of depreciations due to a number of factors. (Mnjama [37]). This made the Central Bank to intervene periodically to smooth out volatility. Speculation on the shilling eased from September 2004 following a positive assessment of the economy by IMF. Hence, from December 2004 to December 2007, its real exchange rate appreciated by 30% representing a major deviation from its past levels. According to Kiptui and Kipyegon [38], this appreciation of the shilling real exchange rate has attracted public attention especially from exporters who have argued that the strengthening shilling is eroding their competitiveness. However, due to the global financial crisis, NEER declined by 1.1% between 2007 and 2008 and by 16.6% between 2008 and 2009 (CBK [33]).

4 Data and Methodology

4.1 Data

Exchange rate behavior is driven by market microstructure considerations rather than traditional economic fundamentals. As such, time duration between trades is important and might contain useful information about market microstructure (Mende [39]; Goyal [40]). In view of this, high frequency data on daily exchange rates were employed. The entire data period is from January 1, 2006 to July 13, 2012, a total of 1,630 observations (excluding holidays).

For the purpose of our analysis, the pre - crises period is from January 1, 2006 to December 31, 2007. Following Ntwiga [14] the beginning of the election violence was presumed as January 1, 2008. According to Mwege [16], among others, both the election violence and the financial crisis occurred simultaneously in Kenya, so it will be difficult (if not impossible) to disentangle the effects of one from the other; hence we defined the crises period from January 1, 2008 to March 31, 2009. The rest of the data is the “post-crisis” period. Datasets on daily

exchange rates of US dollar to the Kenyan shillings were obtained from the official website of the Bank of Kenya. The daily exchange rates used in this study are the average of the buying and selling rates.

Exchange rate returns r_t for each of the three periods were calculated using the formula

$$r_t = \ln\left(\frac{y_t}{y_{t-1}}\right) * 100 \quad (4.1)$$

Where t is the period (in days), y_t and y_{t-1} represent the exchange rate prices for days t and $t-1$ respectively and r_t is the exchange rate return for day t .

The transformation from absolute prices y_t to returns r_t is justified by noting that it is more appropriate to base volatility measures on returns rather than absolute price movements. Level of prices experiences significant changes from time to time (Rahman et al., [41]). Moreover, absolute prices often display unit-root behaviour and thus cannot be modeled as stationary.

4.1.1 Statistical Properties of Data

The summary statistics of the exchange rate returns is given in Table 2. The result indicates that the data under study is skewed to the right, and leptokurtic. This agrees with Maana *et al.* [42] which found evidence of unconditional leptokurtosis in Kenyan shillings. Additionally, result also suggests that Kenyan shillings exhibit some level of volatility, about 59%. Jarque-Bera statistics was highly significant, which implies that the distribution of Kenyan shillings is not normal. Furthermore, the Ljung-Box Q-statistic for both squared and un-squared residuals denoted $Q^2(20)$ and $Q(20)$, respectively are reported in Table 2. Notice that both statistics are highly significant. This suggests that the exchange rate returns depend on past values, i.e. are serially correlated, and that the residuals are strongly heteroscedastic. Using the correlogram as guide the author found that

including lags 1, 2 and 4 in the mean equation effectively reduced the serial correlation earlier reported. The issue of heteroscedasticity will be addressed in the next section using GARCH-type models.

4.2. Methodology

Conditional heteroskedasticity models have been widely used in the literature to evaluate time-varying volatility; see Bollerslev *et al.* [6] for a survey of the literature. Some of the commonly used ones include the GARCH of Bollerslev [43], Asymmetric GARCH (A-GARCH) of Engle [44], EGARCH of Nelson [15], Asymmetric Power ARCH (A-PARCH) of Ding *et al.* [45], GJR-GARCH of Glosten *et al.* [46], Threshold GARCH (T-GARCH) of Zakoian [47], and the Asymmetric Nonlinear Smooth-Transition GARCH (ANST-GARCH) of Anderson *et al.* [48]. EGARCH model is usually preferred in modeling because it provides a specification that allows for asymmetry and volatility changes to be measured simultaneously. In addition, it can capture large shocks of any sign in a financial series, such as the one observed during currency crisis (Baharumshah and Hooi [28]).

4.2.1. EGARCH Model Specification

For each integer t , let r_t be defined as in Equation (4.1), z_t be a sequence of i.i.d random variables, ε_t be the model's prediction error, σ_t^2 is the conditional variance of ε_t , ω , α_i ($i = 1, 2, \dots, p$) and β_j ($j = 1, 2, \dots, q$) are parameters, a univariate Generalized Autoregressive Conditional Heteroscedasticity model, GARCH(p,q), model is

$$\left. \begin{aligned} r_t &= c + \varepsilon_t \\ \varepsilon_t &= \sigma_t z_t \quad \text{where } z_t \sim \text{i.i.d} \quad \text{with} \\ E(z_t) &= 0, \quad \text{Var}(z_t) = 1, \quad \text{and} \\ \sigma_t^2 &= \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \end{aligned} \right\} \quad (4.2)$$

In model (4.2), α_i reflects the influence of random deviations in the previous period on σ_t , whereas β_j measures the part of the (realized) variance in the previous period that is carried over into the current period. The sizes of the parameters α_i and β_j determine the short-run dynamics of the resulting volatility time series. Large error coefficients, α_i , mean that volatility reacts intensely to market movements. Large lag coefficients, β_j , indicate that shocks to conditional variance take a long time die out, so volatility is persistent. The conditional variance in the EGARCH model proposed by Nelson [15] is given following Eviews specification by Quantitative Micro Software (2010),

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^q \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \quad (4.3)$$

(In EGARCH, equation (4.3) replaces the last equation in the system (4.2)).

The presence of leverage effect is indicated by inclusion of the term γ_k and the impact on the conditional variance is asymmetric if $\gamma_k \neq 0$. When $\gamma_k < 0$, then positive shocks (good news) generate less volatility than negative shocks (bad news). When $\gamma_k > 0$, it implies that negative shocks generate less volatility than positive shocks. In other words, A negative value of γ_k implies that negative innovations or news lead to a higher subsequent increase in the volatility of the exchange rate compared with positive news. Hence, an appreciation of the domestic currency relative to the foreign currency tends to induce a higher increase in volatility of the domestic currency than a depreciation of the same magnitude in the subsequent period (Kahya, *et al.* [4]; and Kocenda and Valachy

[5]).

Studies have shown that financial returns are leptokurtic and highly skewed (Hsieh [49]); hence, cannot be modeled with the normal distribution. In exchange rate modeling, the most used alternative is the generalized error distribution (Olowe [11]). Under the assumption that the distribution of $z_t = \frac{\varepsilon_t}{\sigma_t}$ followed the Generalized Error Distribution (GED), the log-likelihood function of GARCH-type models is (Hamilton [50])

$$L_T = \sum_{t=1}^T \left(\ln\left(\frac{\nu}{\lambda}\right) - \frac{1}{2} \left| \frac{z_t}{\lambda} \right|^\nu - \left(1 + \frac{1}{\nu}\right) \ln(2) - \ln \Gamma\left(\frac{1}{\nu}\right) - \frac{1}{2} \ln(\sigma_t^2) \right), \quad (4.4)$$

where

$$\lambda = \left(\frac{2^{\left(\frac{2}{\nu}\right)} \Gamma\left(\frac{1}{\nu}\right)}{\Gamma\left(\frac{3}{\nu}\right)} \right)^{\frac{1}{2}} \quad (4.5)$$

The density of a GED random variable normalized to have a mean of zero and a variance of one is given by:

$$f(z_t) = \frac{\nu \exp\left(-\frac{1}{2} \left| \frac{z_t}{\lambda} \right|^\nu\right)}{\lambda 2^{\left(1+\frac{1}{\nu}\right)} \Gamma\left(\frac{1}{\nu}\right)} \quad -\infty < z_t < \infty, \quad 0 < \nu \leq \infty, \quad (4.6)$$

Where $z_t = \frac{\varepsilon_t}{\sigma_t}$, $\Gamma(\cdot)$ is the gamma function, λ is as defined in (4.5), and ν is tail thickness parameter. When $\nu = 2$, has a standard normal distribution. For $\nu < 2$, the distribution of z_t has a thicker tail than the normal and for $\nu > 2$, the distribution of z_t has thinner tails than the normal (Hamilton [50]).

Under sufficient regularity conditions, the maximum likelihood estimator is consistent and asymptotically normal (Nelson [15]). GARCH(1,1) and

EGARCH(1,1) specifications are employed despite the existence of higher order GARCH specifications on the strength of empirical evidence such as Hsieh [49] and Malik [51] that they are parsimonious and most common specification of GARCH models that sufficiently characterise the behaviour of the exchange rates (Kocenda and Valachy [5]; and Harrathi and Mokhtar [52]). The model parameters are estimated using the maximum likelihood procedure coupled with Marquardt modifications. The relevant variance equations are

1) Full sample without dummy variable C

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (4.7)$$

2) Full sample with dummy variable C

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \theta C \quad (4.8)$$

Where t is the period (in days), θ is the dummy variable coefficient and C the dummy variable which takes value 1 during the crises and 0 otherwise, and β , α , γ and θ are parameters to be estimated. Notice that the same variance equation (4.7) is estimated in both subsamples. The only difference is the span of each period.

5 Main Results

We have divided this section into two parts for clarity. The first part analyzes the full sample period using dichotomous-EGARCH model while the second part compares the variance equations obtained from the subsamples.

5.1 First Part

The maximum likelihood parameters were computed using Eviews 7. The adopted convergence criterion is 1×10^{-10} . Since the dataset is leptokurtic (See Table 2), ν was fixed at 1.5 for ease of comparison between the models. Table 3 lists the parameter estimates for GARCH(1,1) and EGARCH(1,1) exchange rate model for 2006 – 2012 with the inclusion of variable coefficient θ measuring the presence (or absence) of the effect of both Kenyan election violence and the 2008-09 financial crisis.

Next we examine the empirical issues raised earlier in the section:

EGARCH model (though unstable) detected asymmetric volatility in Kenyan shillings: γ was positive and highly significant ($p \approx 0.01$). However, with $\hat{\alpha} + \hat{\beta} = 1.382766$, one cannot rely on estimated values given by EGARCH. (For robustness of results, we also obtained parameter estimates under the t-distribution assumption, EGARCH was also not stable.) The present study however, has succeeded in establishing the possibility of asymmetry in Kenyan shillings; suggesting that volatility tends to rise when return surprises are positive. This research may therefore be pursued further using some other variants of asymmetric models like GJR-GARCH, TGARCH, etc.

For purposes of interpretation, the following discussion is based on the estimated GARCH(1,1) model only.

- (i) While the estimated effect of the crises on returns is positive but insignificant, that of conditional variance is about 2.194×10^{-6} with a standard error of 6.76×10^{-7} . Comparing with earlier result, Olowe [11] also reported a positive insignificant effect of the global financial crisis on the Nigerian FOREX returns but a significant negative estimate for the variance equation. In a nutshell, the inference here is that both election and the global crises had significant effects on the conditional volatility and the estimated effect is

about $2.194 \times 10^{-4}\%$. This provides additional evidence that Africa is not insulated from the rippling effects of the US-triggered crisis.

- (ii) The estimated value of α in Table 3 seems to show that aggregate ARCH effects are not well pronounced, however $\hat{\beta} = 71.1\%$ clearly indicates strong volatility persistence. This is expected since, on aggregate, the crises lasted for over a year consequently; the conditional volatility will (on the aggregate) be driven more by shocks from the crises than by the market movements.
- (iii) Figures 1 and 2 plot σ_t (the conditional volatility of returns) and the Kenyan FOREX rates for the period January 1, 2006 to July 13, 2012, respectively. σ_t exhibits variations with lows of less than one-half and highs over ten. Notice that major episodes of high volatility are associated with market rise.

Specification Tests: Correct specification of GARCH-type models has implications for the returns (Nelson [15]). Accordingly, we test for serial correlation in the standardized residuals and the squared standardized residuals at lags one through twenty.

Table 3 also reports the Ljung-Box Q-statistic with 20 lags (denoted Q(20) and $Q^2(20)$) for e_t and their associated p-values; and in addition, ARCH ML test statistic with 20 lags (denoted ML(20)). In the Ljung-Box test, GARCH model did well, with probability values of 0.099 and 0.949 for Q(20) and $Q^2(20)$, respectively. Meaning that the serial correlation found in the datasets earlier (See Table 2) has been significantly reduced and ARCH effect removed (almost) entirely; giving justification for the specified model. We note here that the serial correlation level (measured by Q(20)) could be reduced further with the inclusion of lags 6, 10 and 14 in the mean equation. However, we did not include them in this computation because such inclusion did not alter (significantly) the estimated values; hence, they would only reduce the degrees of freedom with no added 'advantages'.

5.2 Second Part

This section provides in-depth analysis of the crises, in the sense that the entire period is divided into subperiods: pre-crises, crises. The attention here is actually on the individual impact of the election violence and the global financial crisis on Kenyan FOREX volatility. The essential parameters of the volatility equations shall be analyzed for possible changes. Table 4 presents the parameter estimates for the subsamples.

Estimates of α suggested that volatility reacted more intensely to market movements than to shocks during the pre-crises and election violence periods. This is expected since the market was (averagely) less volatile during the pre-crises period (See Figure 2) and the election shocks lasted for just two months. Consequently, during these periods, conditional volatility is expected to be more influenced by market movements than by shocks.

$\hat{\beta}$, on the other hand, indicated that shocks to conditional variance took longer time to die out during the US-induced global crisis period compared to other periods. More to the point, volatility was more persistent in the global crisis period than that of election with a difference of $0.8896 - 0.4477 = 0.4419$, or equivalently, 44.19%: Election violence started in January 2008 and ended a month after, when the warring parties signed the peace agreement on 28th February, 2008. Thus one would expect that shocks from election violence will be short-lasting compared to that of global crisis which went on for almost a year. Consequently, conditional volatility will be driven more by shocks than by market movements in the global crisis period.

6 Labels of figures and tables

Table 1: KOF Globalization Index for Africa (Average)

	1970-79	1980-89	1990-99	2000-09
Central Africa	24.07	29.11	32.09	39.93
East Africa	22.22	24.66	33.18	43.07
South Africa	48.86	51.63	54.43	59.10
West Africa	24.16	29.25	35.84	44.16
Sub-Sahara Africa	29.83	33.66	38.88	46.57
World	41.09	44.26	51.33	60.48

Source: konjunkturforschungsstelle (KOF), Swiss Economic Institute Database 2010, ETH, Zurich, Germany.

Table 2: Summary Statistics of Kenyan Exchange Rate Return
(January 1, 2006 – July 13, 2012)

Statistics	Values
Mean	0.009133
Standard Deviation	0.590059
Skewness	0.012617
Kurtosis	17.41909
Jarque-Bera	14111.95 (0.00)
Q(20)	69.886 (0.00)
Q ² (20)	998.60 (0.00)

Q(20) and Q²(20) denote the Ljung-Box Q-statistic with 20 lags for the standardized residuals and the squared standardized residuals, respectively. P-values are in parentheses.

Table 3: Parameter Estimates of GARCH-GED and EGARCH-GED models with dummy variable θ , (January 1, 2006 – July 13, 2012).

Parameter	GARCH	EGARCH
c	-1.67E-05 (0.8124)	4.55E-05 (0.5239)
Lag1	0.144121 (0.00)	0.150553 (0.150553)
Lag 2	-0.084323 (0.0045)	-0.070238 (0.0107)
Lag 4	0.021367 (0.4098)	0.023897 (0.3215)
θ	0.000432 (0.1940)	0.000490 (0.1235)
ω	7.40E-07 (0.00)	-1.326990 (0.00)
α	0.261782 (0.00)	0.469293 (0.00)
γ	NA	0.043791 (0.0123)
β	0.710609 (0.00)	0.913473 (0.00)
θ	2.19E-06 (0.0012)	0.124766 (0.00)
$\alpha + \beta$	0.972391	1.382766
Q(20)	28.448 (0.099)	-
Q ² (20)	10.892 (0.949)	-
J-B	2332.087 (0.00)	-
ML(20)	10.16510 (0.9651)	-

Q(20) and Q²(20) denote the Ljung-Box Q-statistic with 20 lags for the standardized residuals and the squared standardized residuals, respectively. LogL is the loglikelihood, J-B denotes Jarque-Bera, ML(20) denotes the ARCH ML test statistic with 20 lags. p-values are in parentheses. NA means Not Applicable.

Table 4: Parameter Estimates of GARCH-GED model: Pre-crises and Crises
(Election and Global) Subperiods.

Parameters	Pre-crises	Crises	
		Election	Global
ω	2.11E-06 (0.00)	5.09E-05 (0.3221)	6.90E-07 (0.2640)
α	0.304510 (0.00)	0.413203 (0.3211)	0.088133 (0.0241)
β	0.483416 (0.00)	0.477746 (0.2434)	0.889950 (0.00)
$\alpha + \beta$	0.787926	0.890949	0.978083
Q(20)	25.710 (0.176)	8.3190* (0.598)	2.8720* (0.984)
ML(20)	5.959042 (0.9990)	3.323534* (0.9728)	14.70604* (0.1432)

*denotes that those values are evaluated at Q(10) and ML (10) (due to sample size).

p-values in parentheses.

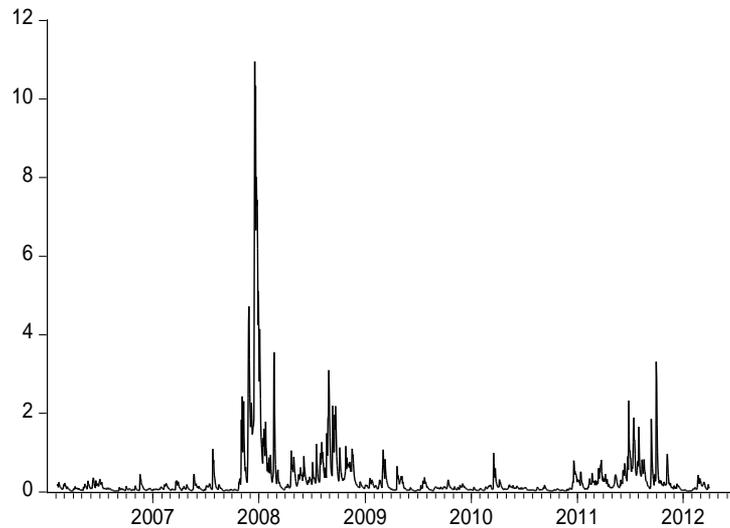


Figure 1: Daily Volatility



Figure 2: Kenyan FOREX rates (January 1, 2006 to July 13, 2012)

5 Conclusion

The study investigates the effect of the election violence and the recent global crisis on the exchange rate volatilities of Kenyan shillings using symmetric and asymmetric volatility models. Though test of diagnostics favoured GARCH model, EGARCH suggested the possibility of asymmetric volatility in Kenyan shillings in which volatility tends to rise when return surprises are positive. Other major findings include the following: First, the election violence and the global crisis both had impact on the returns and the conditional volatility; (on aggregate) estimated effect of both crises on returns is about 0.00043 (though insignificant), and that of conditional variance is about 2.194×10^{-6} with $p < 0.01$. Second, the estimated values of the ARCH and GARCH effects clearly indicated that the conditional volatility (on aggregate) reacted more intensely to shocks than to the market movements. Third, the subsample comparisons showed that while the conditional volatility reacted more intensely to market movements (than to

shocks) during the pre-crises and election periods, it was more influenced by the shocks in the global crisis period.

It should be noted that one of the major benefits of a study like this is to provide policy makers and investors in Kenya with country-specific information on the state of the currency market so that adequate mechanism can be put in place with a view to restoring and sustaining the consistent regional and economic growth that Kenya had experienced prior to the crash (IMF [53]). The following are some recommendations:

Despite the fact that the fundamentals of companies and banking system in Kenya remained strong (See Mwega [16]), yet most foreign and domestic investors opted out of the market owing to the news they received on credit crisis in US, UK, etc. This provides additional evidence that investors usually make decisions based on what they hear. Therefore, continuous communication to public, through media, by regulators, related government officials to provide position on the ground, shape, opinion and perception of the market is very important in order to restore market confidence, attract FDI/ Private capital inflows and investments and promote economic growth. In other words, measures to make the public more knowledgeable should be adopted so that they make informed investment decision. An informed investor is a protected investor.

Second, according to the Ben Ltaifa *et al.* [17], the key lessons that would reduce future risks and vulnerabilities to financial crisis are recognizing the importance of the credibility of the exchange policy, adequacy of reserves, sound debt management, proactive bank supervision and regulation and sound macroeconomic policies in response to cyclical developments. Recall that Asian banks escaped significant impact of crisis (largely) due to well capitalized banks, cautious regulation and huge FOREX reserves (Baharumshah and Hooi [28]).

This present lull in the economy provides an opportunity for CBK and other relevant bodies to implement effective economic policies in order to ensure internal short-term and long-term economic growth. Kenya and Sub-Saharan

Africa, in general, had experienced relatively substantial economic growth before the global financial crisis, and it is important that it continues to grow in order to meet Millennium Development Goals and further alleviate poverty.

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