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An Analysis Of The Volatility Of African Short-term Interest Rates Using A Component GARCH Model

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An Analysis Of The Volatility Of African Short-term Interest Rates Using A Component GARCH Model

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Abstract

This study examines the volatility of Treasury bills in five African countries using the Component GARCH model so as to develop a greater understanding of these instruments. All securities were identified to exhibit highly persistent (non-stationary) volatility, which predominantly comprised of the long-run persistence of historical shocks, as the influence of shocks on the transitory component of volatility reverts to the long-run rate within one to four weeks. In only two of the countries was the response of volatility to innovations asymmetric, whilst volatility risk was identified to be a priced factor in only South African and Kenyan Treasury bill returns.

Key words: *CAPM, risk-free rate, volatility risk, GARCH, Component-GARCH.*
JEL Classification: *C58, D53, E43, G12*

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1. INTRODUCTION

The default-free short-term interest rate is a fundamental concept to most theoretical and empirical finance (Brenner, Harjes and Kroner, 1996: 85; Lanne and Saikkonen, 2003: 96); with the three-month Treasury Bill (T-Bill) rate considered an appropriate measurement thereof. T-Bills are an important component of a country's financial system and represent a critical component of central banks' monetary policy. They act as a benchmark interest rate and form part of the yield curve, which conveys important information for monetary policy (Biepke, 2004: 75). For investors, traders and financial managers the T-Bill rate is crucial to pricing bonds, interest rate derivatives and hedging interest rate risk (Brenner *et al.*. 1996: 85). In many cases, faced with a market unwilling to take up long-term paper, and desiring to borrow at lower rates if the yield curve is significantly upwardly sloping, governments in Africa have tended to rely extensively on short-term debt finance. Three-month bills, for example, represent almost 50 percent of domestic debt in non-CFA[3] sub-Saharan African countries (Christensen, 2004: 14).

T-Bills are also typically advocated as a proxy for the true risk-free rate (see for example Reilly and Brown, 2009: 206; Gitman *et al.* 2010: 230) and as such they are used to estimate the real interest rate for a country, a country's sovereign risk premium, and are used as an important input in asset pricing models such as the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT). In theory, for an asset to be risk-free in an uncertain environment the variance must equal zero for the duration of the investment, implying that the actual returns earned over the period are always equal to the expected return (Sharpe, 1964: 431; Reilly and Brown, 2009: 206). In reality, however, "there is really no such thing as a truly riskless asset" (Brigham and Ehrhardt, 2005: 312). T-Bills are not perfectly risk-free, and changing market conditions can result in great risk to governments having to roll over short-term debt three or four times a year (Christensen, 2004: 14). Furthermore, volatility in T-Bill rates has implications for their suitability as a proxy for the risk-free asset.

Given its importance, considerable research has been conducted on the United States (U.S.) T-Bill rate, in particular, the modelling of its volatility. This has largely occurred over the past two decades as developments in time series analysis techniques, such as the Autoregressive Conditional Heteroscedasticity (ARCH) and Generalised Autoregressive

[3] Non-CFA refers to those countries which do not have the CFA (Franc de la Coopèration Financiére en Afrique) franc as their official currency.

Conditional Heteroscedasticity (GARCH) models, allow the relationships between volatility and price data to be examined (Engle, 2001: 157). No research however, has been conducted on African T-Bill securities; and yet an improved understanding of the volatility of T-Bill rates in Africa is of great practical and theoretical importance. Thus, this paper seeks to apply these volatility modelling techniques to T-Bill data for Ghana, Kenya, Mauritius, South Africa and Zambia, as an initial step in developing a better knowledge of the volatility of default-free short-term interest rates in Africa and the implications thereof for their use in numerous applications.

The remainder of this paper is structured as follows: in Section 2 a brief literature review of studies of volatility is provided; whilst Section 3 contains a summary of the ARCH/GARCH specifications used to model volatility. In Section 4, the data and summary statistics are examined, with the results of the empirical analysis presented in Section 5. Finally, the conclusions and policy recommendations are provided in Section 6.

2. VOLATILITY IN ASSET RETURNS

In examining the stationary returns of many financial series, such as interest rates, shares or exchange rates, a common characteristic that has been identified is that volatility occurs in bursts; that is, large movements in the price of the assets are followed by large movements in either direction and small movements are clustered with small movements (see Bollerslev *et al.*, 1992: 2963; Brooks, 2009: 380). Thus volatility exhibits an auto-regressive structure as the current period value is dependant upon previous values, with shocks persisting. This pattern however is not unexpected, as both traditional financial theory and behavioural finance suggest that current price changes will be determined by changes in previous periods, either in the opposite direction allowing for mean-reversion or correction, or in the same direction as a consequence of herding behaviour (Samouilhan, 2007: 100).

The primary regression method utilised by econometricians, Ordinary Least Squares (OLS), is based on the assumption that the variance of the residuals of an estimated series must be the same at all points; known as homoscedasticity (Brooks, 2009: 386). If this assumption is violated, known as heteroscedasticity, the estimated regression coefficients will be unbiased but not efficient. Clearly, the presence of volatility clustering in financial series contravenes this requirement; thus preventing OLS from being reliably applied to the conditional mean equation. To overcome this characteristic of financial data, the ARCH/GARCH family of models were developed which, rather than considering heteroscedasticity a problem to be rectified, treat heteroscedasticity as a variance to be modelled in addition to the conditional mean equation (Engle, 2001: 157). Accordingly, not only are the deficiencies of OLS accounted for, but estimates of the variance are calculated and can be analysed.

Since the development of the ARCH family of models, they have been employed in a variety of applications such as examining the volatility of share markets, exchange rates and interest rates as well as spillover effects from one market to another. Engle, Lilien and Robins (1987) examined the interest rate differential between six-month and three-month U.S. T-Bills using an ARCH in mean (ARCH-M) formulation in their seminal paper on the model. This model allows for a feedback mechanism between the conditional mean and variance equations. Engle *et al.* (1987: 399) confirmed the presence of volatility clustering in the interest rate differential, with the coefficients in the conditional variance equation highly statistically significant. Moreover, a significant risk premium in the yield spread was identified, indicating that as the spread becomes more volatile investors require a greater return differential between short-term and longer-term T-Bill instruments. Similar results were obtained for a comparison of the yield spread between two-month and one-month T-Bills; however the spread between AAA corporate bonds and the three-month T-Bill did not reveal a statistically significant risk premium (Engle *et al.*, 1987: 404-405).

Engle, Ng and Rothschild (1990) also examined excess T-Bill returns (excess over the one-month T-Bill rate), but using a Factor ARCH model. The Ljung-Box and Ljung-Box squared test statistics confirmed that these interest rate series are categorised by volatility clustering (Engle *et al.* 1990: 222). Before estimating the Factor-ARCH model, Engle *et al.* (1990: 226) estimated a GARCH-M model. The coefficients in the conditional variance equation indicated that volatility was highly persistent (sum of coefficients close to 0.9) and that a significant risk premium in the yield spread existed (Engle *et al.,* 1990: 226). With the Factor-ARCH model, Engle *et al.* (1990: 227-234) found that it models the T-Bill spreads more accurately than the basic GARCH model as the diagnostic checks of the efficacy of the models favour this specification.

Chan *et al.* (1992) examined a number of derived models to compare their ability to model the short-term interest rate (the one month U.S. T-Bill). Rather than allowing the conditional variance to be dependant upon previous values of the volatility, as per the ARCH/GARCH specifications, these models consider how much the volatility depends on previous levels of the interest rate; a factor considered to be important in previous research (see for example

Merton, 1973 and Cox, Ingersoll and Ross, 1985). Lanne and Saikonnen (2003), however, argue that whilst there is evidence in support of the fact that the volatility of interest rates is a function of the level of the past interest rate, volatility also depends on previous period volatility (volatility clustering), and thus models of the short-term interest rate in the U.S. should incorporate both of these characteristics. Following Lanne and Saikkonen (2003), Venkatesh (2006: 9), in a similar analysis to Chan *et al.* (1992) of the London Interbank Offering Rate, identified that whilst the level of the interest rate is an important determinant of the volatility of the returns, the previous period values and historical shocks are equally important.

From a developing market perspective, Irfan *et al.* (2010: 1092) examined the volatility persistence of the Karachi and Mumbai Interbank Offering Rates (KIBOR and MIBOR respectively). They found that the volatility of the former is highly persistent (non-stationary), whilst for the short-term Mumbai security, it is also persistent but remains stationary. The KIBOR is seen to exhibit a substantial leverage effect, signalling that negative shocks cause greater volatility in the series than positive shocks of a similar magnitude.

As far as African is concerned, there are a number of studies which have considered the volatility of various share markets in the continent. Using the “in-mean” framework of Engle *et al.* (1987), Mangani (2008) and Mandimika and Chinzara (2010) find that overall volatility is not a priced factor on the Johannesburg Securities Exchange (JSE). With respect to leverage effects, there is some disagreement, with Mangani (2008) observing that volatility responds symmetrically to both good and bad news announcements, whilst Chinzara and Aziakapono (2009), Chinzara (2010) and Mandimika and Chinzara (2010) identify that the volatility of the JSE and its four main sectors is inherently asymmetric.

Mangani (2008), Chinzara and Aziakpono (2009) and Chinzara (2010) find that the South African equity volatility is highly persistent, with estimates for the overall market close to 0.9. In fact, for some sectors and individual shares, it is even found to be non-stationary, with Mandimika and Chinzara (2010) obtaining estimates for the entire All Share Index which indicate non-stationary volatility. Samouilhan (2007) to address this potential problem uses a Component GARCH model to examine the non-stationary variance associated with South African share returns.

Magnus and Fosu (2006) consider the appropriateness of the GARCH, Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH) models for the Ghanian market. Volatility is identified to be highly persistent (non-stationary) and whilst there is some evidence of asymmetric responses in volatility to shocks, the differences are not statistically significant. Nyanmango and Misati (2010) examine the volatility of shares listed on the Kenyan stock exchange and find that whilst volatility is highly persistent, it is still stationary and there is no evidence of leverage effects[4].

Despite a considerable number of studies on stock market volatility in Africa, there is a dearth of research examining the volatility of African short-term interest rates comparable to those that have been conducted globally. This paper employs the ARCH/ GARCH framework to provide an analysis of the volatility of T-Bill returns for several African countries as an initial step in remedying this deficiency.

3. MODELLING VOLATILITY

3.1 The GARCH Model

In applying the ARCH/GARCH model to the variance of the series, it remains necessary to define an appropriate conditional mean equation determined by the research objective of the study. Given that the goal of this research is to explicitly examine the conditional variance of the T-Bills; an autoregressive (AR) specification with one lag and an intercept was adopted for each of the T-Bill series. However, in accordance with the ARCH-M model developed by Engle *et al.* (1987), the square root of the conditional variance was also included as a determinant of the T-Bill returns; thus providing a feedback mechanism from the conditional variance equation. In so doing, the coefficient on the conditional variance term in the mean equation can be interpreted as a risk premium; the greater the risk, as measured by the conditional variance, the greater the return should be. The formula used for the conditional mean is shown is equation 1 (Engle *et al.*, 1987: 400).

$$R_t = \lambda_0 + \lambda_1 R_{t-1} + \delta\sigma_t + \varepsilon_t \qquad (1)$$

Where:

- R_t are the returns of the asset
- σ_t is the square root of the conditional variance (σ^2_t)
- ε_t is the residual

[4] For a detailed list of other similar studies of African market volatility see Nyanmango and Misati (2010).

The GARCH model is generally favoured for modelling the conditional variance rather than the ARCH model, as it provides a more parsimonious specification that is easier to estimate (Engle, 2001: 159) and accordingly, is generally employed in practice. The generalised equation for the conditional variance for a GARCH (1,1) model is shown in equation 2, with the number one denoting a single lag of both the squared error term and conditional variance. This lag structure is widely considered to be sufficient for the purposes of analysing financial data (Bollerslev *et al.*, 1992). The conditional variance in the current period is thus modelled as a weighted average of the long-run variance, the new information in each period and the variance observed in previous periods (Bollerslev, 1986: 309).

$$\sigma^2_t = \omega_0 + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \tag{2}$$

Where:

- ε^2_{t-1} is the previous period value of the squared residuals
- σ^2_{t-1} is the previous period value of the conditional variance

Quasi-maximum-likelihood is normally employed to estimate these equations rather than full-maximum-likelihood, as Bollerslev and Wooldridge (1992) showed that the former provides consistent parameter estimates even if the distribution is non-Gaussian (normal), which is not true for full-maximum-likelihood. Accordingly, quasi-maximum-likelihood is the default estimation method applied in EViews 6, the package which was used for this calculation. Notwithstanding this adjustment, it remains necessary to specify the appropriate distribution of returns for the series.

The majority of relevant studies using GARCH models continue to assume a Gaussian distribution of the error terms, but Koop (1994) argues that such models face the risk of misspecification. Accordingly, studies such as Leon (2008), Kovačić (2008) and Mandimika and Chinzara (2010) estimate the models using a Gaussian, Student's t- and generalised error distribution and select the appropriate distribution with the use of information criteria. None of these studies find that the Gaussian distribution is optimal, yet they differ in terms of the choice between the t- or generalised error distributions; thus highlighting that the appropriate distribution is series-specific. Therefore, in this study the models were estimated using all three distributions and the models compared on the basis of the Schwarz Bayesian Information Criterion (SIC)[5]; with the model with the lowest criterion considered optimal.

A frequently computed measure of the decline in volatility over time is that of the half-life of the past error's influence on current conditional volatility; that is, how long it takes for the influence of a given shock on conditional volatility to decrease by half. Although somewhat arbitrary, absolute measures of decline cannot be computed as the effect of a shock never dies away completely and because the decaying process slows down at a convex rate this measure does capture a significant component of the influence of the shock (Samouilhan, 2007: 105). Moreover, this measure is frequently used as the basis to compare the effects of shocks in different series (Samouilhan, 2007: 113; Reider, 2009: 7) and thus provides a useful tool in comparing the volatility of the various country T-Bills in this study. Equation 3 shows the appropriate formula for when the given shock has declined by half and solving this for the half-life yields equation 4 (Reider, 2009: 7).

$$0.5\,(\varepsilon^2_t) = (\alpha + \beta)^{í}\,(\varepsilon^2_t) \qquad (3)$$

$$í_{HL}(\alpha + \beta) = \ln(0.5)/\ln(\alpha + \beta) \qquad (4)$$

Where: í is the time taken for the influence of the given shock to decline by half.

As mentioned in the previous section, it has been observed in empirical studies that negative innovations have a larger impact on volatility than positive innovations of the same magnitude, known as the leverage effect. Several different specifications of the conditional variance have been proposed to account for this asymmetry such as exponential GARCH (EGARCH) and threshold GARCH (TARCH) (Engle and Ng, 1993: 1750). The TARCH formulation is employed in this study as the adjustments can be included in the conditional variance specification irrespective of the format of the equation. The applicable conditional variance equation is shown in equation 5, where the asymmetrical effect is captured if γ is greater than zero, as the effect on volatility differs depending on the sign of the innovation in the previous period (Engle and Ng, 1993: 1757).

$$\sigma^2_t = \omega_0 + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \gamma\varepsilon^2_{t-1}I_{t-1} \qquad (5)$$

Where: $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ otherwise $= 0$

[5] This criterion was used as the basis for comparison as it imposes a much stricter penalty term than the Akaike Information Criterion (AIC) (Brooks, 2009: 236).

3.2 The Component GARCH (CGARCH) Model

In applying the GARCH model it is imperative that $\alpha + \beta$, known as the mean-reverting or persistent rate, must be less than one (Engle and Lee, 1999: 477). When the latter condition is satisfied, the conditional variance will revert to the mean (the unconditional variance, ω_0) at a geometric rate of $\alpha + \beta$; the smaller the rate, the quicker the influence of historical shocks on volatility dissipates (Samouilhan, 2007: 105). When $\alpha + \beta$ is equal to zero, the effects of shocks die out immediately (i.e. there are no GARCH effects), whereas when the sum is equal to one, the effects of the shocks never die away and the conditional variance is said to have a unit root (Samouilhan, 2007: 105). The latter scenario has been observed for equity, exchange rates and interest rates over long time horizons[6], which thus renders the traditional GARCH specification for modelling the conditional variance inappropriate. Several solutions to this characteristic of financial data have been developed[7], but "… this literature is relatively new and still developing" (Hearn and Piesse, 2009: 53).

The Component GARCH (CGARCH) model (Engle and Lee, 1999), rather than seeking to resolve the problem of the non-stationary volatility as per many of the other models, incorporates this characteristic into the GARCH specification by examining the variance as the sum of two components. Both components are modelled individually as GARCH specifications, with one capturing the short-run effects of shocks and the other the long-run effects. Samouilhan (2007: 110) confirms the usefulness of this approach saying "As a tool used in the understanding of the behaviour of the equities second moments, it is thus a major improvement on the standard GARCH estimation". Accordingly, where the assumption of stationary volatility is violated, the CGARCH model was used in this study.

The conditional variance in the GARCH model exhibits mean reversion to a level of ω_0, whereas with the CGARCH specification the mean reversion occurs to a time-varying level (q_t), which represents the long-run volatility. Equation 6 describes how this long-run component, which converges to ω_0, is modelled; whilst in equation 7 the transitory component of the volatility (the deviation of the current conditional variance from the long-run variance) is shown (Engle and Lee, 1999: 477-478).

$$q_t = \omega_0 + \rho(q_{t-1} - \omega_0) + \varphi(\varepsilon^2_{t-1} - \sigma^2_{t-1}) \qquad (6)$$

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[6] See for example, Bollerslev *et al.* (1992); Engle and Lee (1999); and Lanne and Saikkonen (2003).

[7] Such as Integrated GARCH, Power ARCH, Factor ARCH, Factor Integrated GARCH and Mixture Autoregressive Models.

$$\sigma^2_t - q_t = \alpha (\varepsilon^2_{t-1} - q_t) + \beta (\sigma^2_{t-1} - q_t) \quad (7)$$

In the equation for the transitory volatility, α represents the initial impact of a shock to the transitory volatility and β represents the degree of memory in the transitory component. The sum of these two terms thus provides an indication of persistence in short-run volatility (Wei, 2009: 66); that is, the short-run volatility component mean reverts to zero at a geometric rate of $\alpha + \beta$. Similarly, the value of ρ in the long-run volatility equation provides a measure of the long-run persistence and thus typically lies very close to one indicating that the long-run volatility approaches the mean value very slowly such that the effects of historical shocks persist for a long period. This can be compared to the sum of $\alpha + \beta$ to determine whether persistence is greater or smaller in the long-run or short-run. The conditional variance is stationary if the permanent and transitory volatility are both stationary, which necessitates that ρ and $\alpha + \beta$ be less than one (Engle and Lee, 1999: 479). Finally, the value of φ captures the influence of the driving force from the time-dependant movement of the permanent component (Wei, 2009: 67).

As with the GARCH model, the half-life can still be computed for the CGARCH model, but two distinct measures are calculated. The long-run half-life, based on the estimate of ρ, measures the time taken for the long-run influence of a shock in volatility to decline by half; whilst the transitory half-life accounts for the number of trading periods needed for the shock's rate of declining influence to revert to its long-run rate (Samouilhan, 2007: 108; 115). Equations 8 and 9 show the appropriate formula for the computation of the half-lives (Samouilhan, 2007: 107-108).

$$\acute{\imath}_{HL}(\rho) = \ln(0.5)/ \ln(\rho)$$

(8)

$$\acute{\imath}_{HL}(\alpha + \beta) = \ln(0.5)/ \ln(\alpha + \beta)$$

(9)

The adjustments made in the TARCH model can also be included in the equation for the transitory component of volatility in the CGARCH model to allow for asymmetric responses. This is given as (Engle and Lee, 1999: 486-487):

$$\sigma^2_t - q_t = \beta (\sigma^2_{t-1} - q_t) + \alpha (\varepsilon^2_{t-1} - q_t) + \gamma (\varepsilon^2_{t-1} - q_t) I_{t-1} \quad (10)$$

4. DATA AND DESCRIPTIVE STATISTICS

Given the need for high frequency data when estimating an ARCH/ GARCH model, the countries chosen for this analysis were required to have weekly or bi-weekly auctions for 90 day (three-month) T-Bills. Ghana, Kenya, Mauritius, South Africa and Zambia satisfied this requirement. Botswanan and Tanzanian T-Bills were also initially examined. The Tanzanian security however, did not exhibit ARCH effects and therefore was not considered further given the aim to examine those instruments that display volatility clustering. In contrast, Botswanan T-Bills were identified to exhibit ARCH effects, with the GARCH model being more appropriate than the CGARCH because the volatility was stationary, but the diagnostic tests of the appropriateness of the GARCH model in explaining the data were all statistically significant; thus indicating that the model did not fit the data well. Similar results were obtained when using a CGARCH specification. Thus, although the tests of the ARCH effect signal volatility clustering in the Botswana T-Bill series, the models employed were not able to capture this structure and consequently the Botswanan T-Bill was also not considered in the analysis of results.

Data was captured from the auction records from the respective central bank websites. The availability of these historical auction records for public viewing differed across each country and thus rather than selecting the same starting point for each country, all available data was collected. The varying starting dates are detailed in Table 1. For South Africa however, data is available from 1981. Given that the South African economy has undergone dramatic changes in the past fifteen years, most notably its integration with the global market, it was not considered appropriate to examine this series from the beginning of the data provided. Although no date for financial integration can be pinpointed, the beginning of 1994 was deemed an appropriate cut-off point, in accordance with the findings of Makina and Negash (2004) and Mangani (2007: 65). Moreover, this coincides closely with the dataset for Kenya which dates from January 1995.

From the T-Bill yields the prices of the instruments were computed, with details on the differences between the pricing of the assets obtained from the relevant websites. The returns were then calculated as the first difference in the natural logarithms of the asset prices.

Table 1: Summary Details of Data from Each Country Examined

Country	Time Period	Frequency	Source of Data
Ghana	January 2005 – November 2010	Weekly	Databank Central Bank of Ghana
Kenya[8]	January 1995 – July 2009 August 2009 – November 2010	Weekly Biweekly	Central Bank of Kenya
Mauritius	December 1998 – November 2010	Weekly	Banks of Mauritius
South Africa	January 1994 - November 2010	Weekly	South African Reserve Bank
Zambia	November 2003 – November 2010	Weekly	Bank of Zambia

Table 2 presents descriptive statistics for each series: sample means, standard deviations, skewness, kurtosis and the Jarque-Bera test for normality. The values presented for the standard deviation of each series confirm that the instruments do exhibit variation in returns over time in contravention of the requirements of a risk-free asset, with the lowest volatility exhibited by South African T-Bills. This is not surprising given that the South African market is the most developed of those examined. The mean estimates are higher and the standard deviations lower of the five series than those obtained by Chan *et al.* (1992: 1216) for the U.S. three-month T-Bill and Venkatesh (2006: 9) for the LIBOR. Although the differences in time periods do not make the results directly comparable, the relationship identified conforms to expectations that the instruments of more advanced markets exhibit lower volatility because of the greater degree of development of the U.S. and British economies and the implications thereof for fluctuations in the interest rates to achieve economic and social objectives.

The values of the skewness and kurtosis measurements differ significantly from zero and three respectively and thus indicate that none of the T-Bill returns respond symmetrically to information shocks in the market. The return distributions of Mauritian and Zambian T-Bills are positively skewed; whilst for the remainder the distributions are negatively skewed. The negative skewness of Ghanian, Kenyan and South African T-Bill returns conforms to the findings of Irfan *et al.* (2010: 1090) for the KIBOR and MIBOR, whilst Engle *et al.* (1990: 222) documented positive skewness for the U.S. treasury securities.

[8] The change to bi-weekly auctions in Kenya was not identified to have a significant effect on the results obtained.

Table 2: Summary Statistics

	Ghana	Kenya	Mauritius	South Africa	Zambia
Mean	0.004450	0.005074	0.003870	0.001270	0.018803
Median	0.000000	0.001534	0.002438	0.000000	0.005467
Maximum	0.329647	1.173217	1.325016	0.483171	1.527967
Minimum	-0.890071	-1.261600	-0.850130	-0.557499	-1.435634
Standard Deviation	0.095840	0.128651	0.084766	0.060373	0.204744
Skewness	-3.638894	-0.988474	4.025054	-1.989610	1.415684
Kurtosis	35.40032	34.26319	119.5542	33.29482	23.00734
Jarque-Bera	12774***	32505***	34238***	26375***	6193***

***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

The values of kurtosis reveal that each of the return series is leptokurtic. This is relevant in light of the analysis of securities which are used to proxy for a risk-free asset, as assets which follow a leptokurtic distribution are likely to exhibit lower variance than assets which have platykurtic or normal distributions, as return values are usually clustered around the mean. This finding is consistent with Engle *et al.* (1990) and Irfan *et al.* (2010: 1090). The Jarque-Bera test statistics confirm the observations regarding skewness and kurtosis as the null hypothesis of normality is rejected for all securities. The fact that these securities are not normally distributed implies that arbitrage opportunities exist for traders however, the ability to take advantage of these opportunities is limited by the low returns associated with such instruments.

Given that the evidence points towards a leptokurtic distribution of asset returns, assuming a Gaussian (normal) distribution in applying quasi-maximum-likelihood is unlikely to be suitable. Consequently, as mentioned in Section 2.2, an analysis was conducted to determine the appropriate distribution for each series.

Table 3 contains statistics for tests for ARCH effects (using 12 lags) that are commonly employed in texts and empirical studies; the Engle (1982) Lagrange Multiplier test (ARCH-LM), the Ljung-Box Q (LBQ) statistic for the residuals and squared residuals (LBQ^2) (for example, Engle (2001: 164), Brooks (2009: 209-210 and 389-390) and Wei (2009: 65). The test statistics from the ARCH-LM test are significant at the 1% level for all countries; thereby confirming the presence of heteroscedasticity in the variables. The Ljung-Box Q statistics for both the residual and squared residuals also confirm the presence of autocorrelation. Taken together, these tests signal that the T-Bills exhibit an autoregressive structure in volatility.

The stationarity of the series were investigated using the augmented Dickey-Fuller (1981) (ADF) and Kwiatowski, Phillips, Schimdt and Shin (1992) (KPSS) tests. As can be seen, the tests are consistent with the conclusion that the series are non-stationary in levels (prices) but stationary in first differences. Consequently, the differenced log returns were used as the basis for estimating the conditional mean and variance equations.

Table 3: Tests for ARCH Effects

	Ghana	Kenya	Mauritius	South Africa	Zambia
ARCH-LM (12)	108.67***	113.58***	178.67***	194.03***	168***
LBQ (12)	24.227**	27.218***	28.922***	62.704***	35.628***
LBQ^2 (12)	121.24***	103.43***	129.48***	242.79***	111.64***

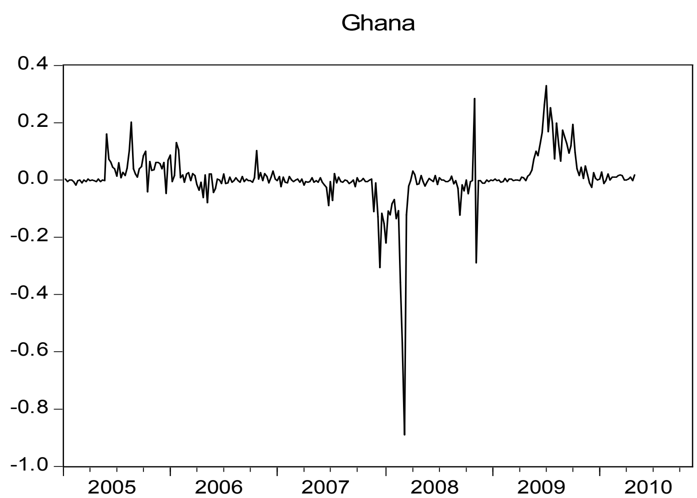
***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

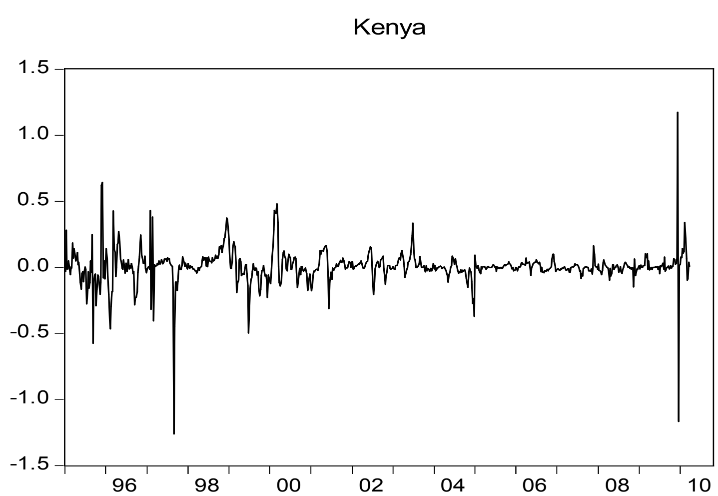
Table 4: Stationarity Tests

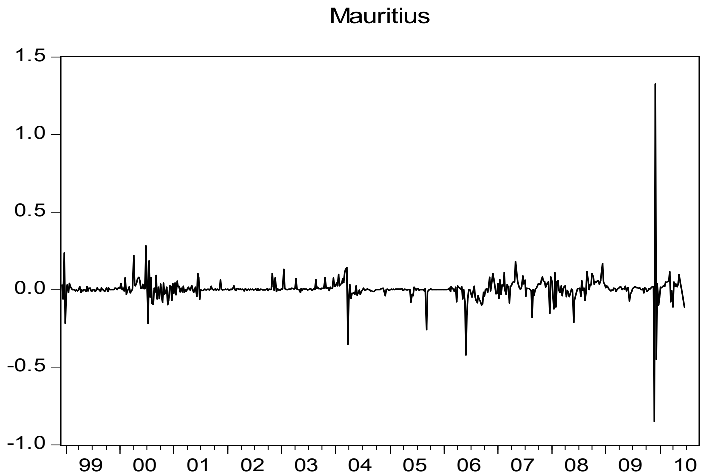
	Ghana	Kenya	Mauritius	South Africa	Zambia
ADF – Level	-1.2083	-1.4318	-0.9641	-1.1740	-1.8198
ADF – 1st Differences	-5.95***	-13.80***	35.72***	-15.06***	-11.55***
KPSS – Level	0.6170**	2.4069***	1.3372***	2.2133***	0.4374*
KPSS – 1st Differences	0.2146	0.0475	0.1011	0.1226	0.1768

Graphs of the stationary returns of each series are depicted in Figure 1, with the weekly returns on the vertical axis and time on the horizontal axis. These securities show some evidence of volatility clustering, with small price changes following small price changes, and large changes following large changes. Except for the South African security however, the volatility clustering does not appear to be as severe as revealed in international studies or those of other African instruments. This observation contradicts the empirical results presented in Table 3, which confirm that these instruments do exhibit significant ARCH effects. The reason this pattern is not clearly evident graphically is because all of these securities are subject to points in time, where either substantial positive or negative returns are earned which thus impacts upon the scale, with the weekly fluctuations being comparatively smaller. The graph of the Kenya T-Bill for example, reflects a negative return of approximately 1.3% from one auction to the next in the latter part of 1997 and in 2010.

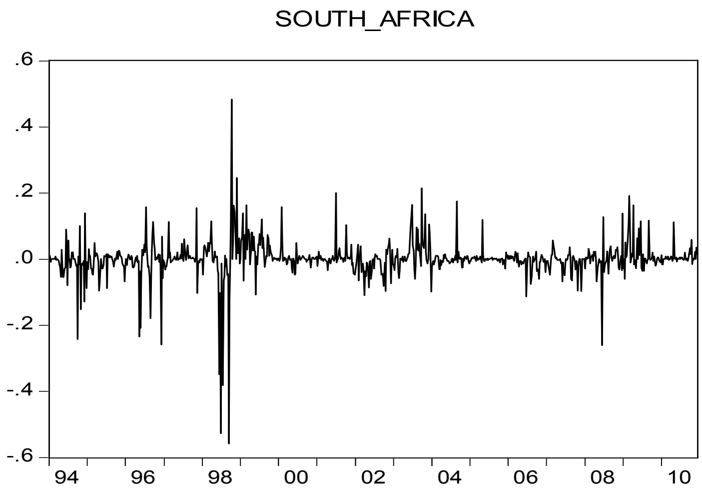
Figure 1: African T-Bill Returns



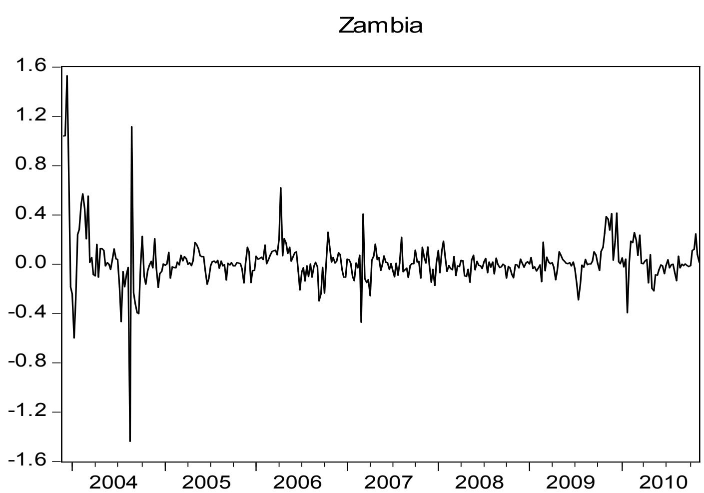




Mauritius
1.5
1.0
0.5
0.0
-0.5
-1.0
99 00 01 02 03 04 05 06 07 08 09 10



SOUTH_AFRICA
.6
.4
.2
.0
-.2
-.4
-.6
94 96 98 00 02 04 06 08 10



Zambia
1.6
1.2
0.8
0.4
0.0
-0.4
-0.8
-1.2
-1.6
2004 2005 2006 2007 2008 2009 2010

5. RESULTS AND ANALYSIS

The conditional mean and variance equations were estimated for each series using the Gaussian, generalised error and Student t-distributions. The model with the smallest SIC was considered optimal and employed for the purposes of this analysis. The Gaussian distribution was not deemed appropriate for any of the series, thus confirming that the asset returns do not closely approximate a normal distribution. As detailed in Table 5, the t-distribution was suitable for all series except South African T-Bills, where the generalised error distribution provided a more pertinent specification.

Table 5: Distribution Comparisons

Distribution	Ghana	Kenya	Mauritius	South Africa	Zambia
Gaussian	-2.498504	-2.281782	-2.880044	-3.328611	-1.257058
Student t	-3.891656†	-3.277110†	-4.069617†	-4.349538	-1.574984†
Generalised Error	-3.866792	-3.257623	-4.051880	-4.451640†	-1.563971

† indicates the model which minimises the SIC.

The GARCH model was estimated initially for each series but in all cases was found to be inappropriate for modelling the conditional volatility of the T-Bills, as the volatility was identified to persist (as seen in the sum of the estimates of $\alpha + \beta$ exceeding one). As mentioned in Section 1, this is consistent with the findings of Irfan *et al.* (2010: 1092) for the KIBOR. For this reason, the CGARCH specification of the conditional variance was thus applied to all country T-Bills.

Before discussing the findings for the respective securities, it is of value to consider the diagnostic checks that were performed in order to test the suitability of the CGARCH model estimated for each of the five T-Bills. The results from these tests are presented in Table 6. As with testing for ARCH effects, the ARCH-LM test for heteroscedasticity and the Ljung-Box tests for serial dependence in the level and squares of the standardised residuals were conducted. None of the test statistics are significant at the conventional significance levels and therefore it can be concluded that the ARCH effects and autocorrelation have been removed. The only exception is that of Ghana, where the Ljung-Box Q statistic for the residuals in level form is significant; but this contradicts the results from the other two tests.

Moreover, given that the Ljung-Box test on the squared residuals examines the variance of the residuals rather than the standard deviation (as per the Ljung-Box Q statistic on the residuals in levels), this test more closely approximates the true definition of volatility and accordingly, can be afforded greater weight. Therefore, the residual diagnostic tests validate that each estimated model produces a white noise process in the residual series.

Table 6: Diagnostic Checks for CGARCH-M models

	Ghana	Kenya	Mauritius	South Africa	Zambia
ARCH-LM (12)	1.779414	0.420802	0.176877	0.224301	0.052760
LBQ (12)	37.946***	17.227	9.2919	16.024	13.117
LBQ^2 (12)	1.7532	0.4293	0.1774	2.7263	0.6863

***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

In light of the success of the CGARCH specification for modelling the five African T-Bills in the diagnostic tests, the parameter estimates and half-life measures can be meaningfully examined. These are shown in Tables 7 and 8 respectively. The asymmetric models were estimated for each but where γ was found to be statistically insignificant, the model was re-estimated without the asymmetric term and consequently, only these results are presented.

5.1 The Conditional Mean Equations

Firstly, in examining the conditional mean equations for each of the securities, it is clear that these securities all exhibit a strong autoregressive structure, as the coefficients on the AR term are highly statistically significant, implying that the returns in the current period are dependant upon returns in the preceding period. Given the nature of the assets examined, this relationship conforms to expectations, with the positive signs confirming that the conditional T-Bill returns in each period are a significant function of the return in the preceding period. The intercept term, which shows the unconditional mean return, is statistically significant for Kenya, Mauritius and South Africa. Thus, although the unconditional mean value is negative for the other two countries, this portion of the return is not statistically significantly different from zero. For South Africa, however, this unconditional mean value of -0.00768 is significant; thereby implying that the unconditional mean value of these securities, which is not a function of past returns or the volatility of the instrument, is negative. This finding is in line with Venkatesh (2006) for the LIBOR.

Table 7: CGARCH-M Parameter Estimates

	Ghana	Kenya	Mauritius	South Africa	Zambia
Conditional Mean Equation					
λ_0	-0.003991 (0.006570)	0.026272** (0.011148)	0.007831*** (0.000972)	-0.000768*** (0.002721)	-0.003026 (0.009276)
λ_1	0.617738*** (0.037536)	0.705354*** (0.020803)	0.329982*** (0.034149)	0.236048*** (0.002721)	0.344805*** (0.052581)
Δ	0.102387 (0.084998)	0.122180** (0.061862)	0.027878 (0.049765)	0.089760*** (0.006548)	0.089173 (0.116550)
Conditional Variance Equation					
ω	0.005267 (0.003698)	0.001795** (0.000907)	0.002041* (0.001160)	0.004806*** (0.000142)	1.357558 (44.66598)
ρ	0.980695*** (0.017338)	0.994151*** (0.001921)	0.944045*** (0.030552)	0.988229*** (0.003881)	0.989419*** (0.052194)
φ	0.309716** (0.127596)	0.009419 (0.012967)	0.559874*** (0.115436)	0.167202*** (0.036589)	0.486722*** (0.137370)
α	0.356352** (0.151032)	0.655787*** (0.051376)	0.217251*** (0.079556)	0.340285*** (0.056255)	0.197739* (0.112572)
β	0.463281*** (0.091995)	0.204264*** (0.050544)	0.593520*** (0.110894)	0.204473** (0.105592)	0.341678 (0.355000)
γ	0.172316* (0.097888)		0.105662** (0.042227)		

***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Table 8: Half-Life Estimates from the CGARCH-M Model

	Ghana	Kenya	Mauritius	South Africa	Zambia
$í_{HL}(\rho)$	36	118	12	59	63
$í_{HL}(\alpha+ \beta)$	3.48	4.5976	3.30	1.14	1.12

As mentioned in Section 3.2, the significance of the risk premium (δ) is of considerable importance in the context of examining assets which are considered risk-free and used as a benchmark rate, as a significant value is indicative of a volatility risk premium included in the yield of the instrument. In this regard, the risk premium term is significant for Kenya at the 5% critical value and for South Africa at the 1% significance level. This finding is surprising in light of the standard deviation figures detailed in Table 2, which indicate that the greatest volatility is associated with the Ghanaian T-Bills and then Kenyan T-Bills; whilst the volatility of South African T-Bills is the smallest of those instruments modelled. Thus, the results obtained cannot be directly attributed to volatility but may reflect economic factors, behavioural characteristics of investors and/ or the government, as well as legislation[9]. These results are similar to the findings of Engle *et al.* (1987) and Engle *et al.* (1990) in that a significant risk premium is identified, but because of the differences in the measure under scrutiny (T-Bills versus T-Bill spreads) the results are not directly comparable.

5.2 The Conditional Variance Equations

As far as the conditional variance equations are concerned, only Ghanaian and Mauritian T-Bills were identified to exhibit a significant leverage effect implying that the response of variance to positive and negative shocks was statistically significantly different, which was not the case for the other instruments. As can be seen from the results, this indicates that negative shocks have a bigger impact on volatility than positive shocks of a similar magnitude because of the positive sign of γ. This finding that some country short-term interest rates are more influenced by negative rather than positive shocks is consistent with Irfan *et al.* (2010). This has important implications for investors holding these instruments as negative shocks in these markets will have greater consequences in terms of contributing to greater volatility than positive shocks of a similar magnitude.

Considering the transitory component of volatility, the estimates of α are positive and statistically significant for all countries; thus signalling that the initial impact of a shock to the transitory component is substantially positive for these T-Bills. The estimates of β are also positive and statistically significant for all the T-Bills, except Zambia. Given that β reflects that the degree of memory in the transitory component, the fact that it is significant

[9] The results obtained cannot be attributed to the longer time period examined with both Kenyan and South African T-Bills compared to the other instruments, as the model was re-estimated using a shorter time period (2004-2010) and significant risk premia were still obtained.

indicates that past values of the transitory volatility are an important determinant of the current period value of the transitory volatility. The sum of these two coefficients provides an indication of the persistence of shocks to transitory volatility. In this regard, transitory volatility is most persistent in Ghana, Kenya and Mauritius, where the sum of $\alpha + \beta$ exceeds 0.8. For South Africa and Zambia, the persistence is considerably lower at approximately 0.54.

These differences are reflected in the transitory half-life figures presented in Table 8, where the influence of past shocks on current period volatility is approximately three-and-a-half to four-and-a-half weeks for the three countries with greater transitory persistence and only just over one week for South Africa and Zambia. Thus, the persistence of volatility reverts to its long-run rate much quicker for South Africa and Zambia; which possibly reflects greater efficiency associated with these markets. Samouilhan (2007: 113), in examining the South African All Share Index 40 (ALSI40), obtained a transitory half-life measure of approximately six days and thus, this seems to suggest that the number of trading days it takes for a shock's rate of declining influence to revert to its long-run rate is similar across these two asset classes in South Africa.

With regards to the determinants of long-run volatility, all the T-Bills have positive intercepts (as expected) but are not statistically significant for Ghana and Zambia. This represents the rate to which the long-run variance converges and consequently, for Ghana and Zambia, this figure does not differ markedly from zero. Obtaining insignificant intercept estimates however, is in accordance with the analysis by Samouilhan (2007) and other studies employing the CGARCH method (Engle and Lee, 1999 and Wei, 2009). The estimates of the long-run persistence, given by ρ, are all highly significant and lie very close to one. This confirms that the volatility mean-reverts at a very slow pace in the long-run. The only country for which this is considerably lower is Mauritius, but the difference is not substantial, as the value is still statistically insignificantly different from one. These high persistence rates translate into half-life estimates for the permanent volatility which are very sizeable, as can be seen in Table 8. The lower estimate of ρ for the Mauritian T-Bills results in a half-life estimate of only 12 weeks, whereas the high persistence of Kenyan T-Bills translates into a massive 118 weeks (or more than two years). For South African and Zambian T-Bills, the measures indicate that the half-life of a past error's influence on conditional volatility is approximately one year (59 trading weeks); again showing the length of time for which shocks have a substantial influence. Interestingly, these half-life estimates do exceed that of

South African equities, for which Samouilhan (2007: 113) computed a half-life measure of just more than half a year (169 trading days). Thus, the South African share market appears to exhibit greater informational efficiency than the comparative short-term bond market. This observation is understandable, however, as greater trading volume (in equity as opposed to bond markets) results in a greater transfer of information and faster adjustments to true asset prices.

These comparisons of the values of transitory and permanent volatility confirm the greater persistence of volatility in T-Bills in the long-run and how these instruments differ quite markedly in terms of responses to shocks. Furthermore, the combined evidence in the transitory and permanent volatility equations reveals that volatility is stationary as the persistence measurements in each equation satisfy the criterion of being less than one.

Finally, the estimates of φ are positive and statistically significant for all T-Bills except for Kenya, which captures the influence of the driving-force from the time-dependant movement of the permanent component.

6. CONCLUSION AND RECOMMENDATIONS FOR FURTHER RESEARCH

Short-term government bills play an important function in any market given their use as a tool of monetary policy, their role in pricing longer-term debt instruments and derivatives, and in the determination of the yield curve. In addition to this, because they most closely resemble the ideal of a default-free short-term instrument, T-Bills are typically advocated as a proxy for this rate in asset pricing models. Accordingly, T-Bills have over the years garnered much attention in the U.S. literature, particularly their volatility, as assets which are used to model the risk-free rate should have constant volatility. But very little research has been conducted on these instruments in an African context and thus this study sought to examine the volatility of three-month T-Bills of Ghana, Kenya, Mauritius, South Africa and Zambia.

These assets, like many other financial instruments, were identified to exhibit volatility clustering (or ARCH effects) and thus GARCH models were employed to examine the variance of the instruments. The volatility of the T-Bills was found to be highly persistent (non-stationary) and thus the CGARCH model was used. The “in-mean” extension to the models was also evaluated.

The results of this analysis revealed that although the same instruments from each country were examined, they exhibit very different volatility structures. In particular, the results showed that in only Mauritius and Ghana negative shocks have a bigger impact on volatility than positive shocks of a similar magnitude; that the transitory persistence was quite low for all T-Bills but especially for the South African and Zambian securities; that the long-run persistence of shocks to volatility was substantial for these instruments, with the half-life measures of the decline in influence of historical shocks ranging from 12 weeks for Mauritian T-Bills, to 36 for Ghana, approximately 59 weeks for South African and Zambian T-Bills and a massive 118 weeks or approximately two years for Kenyan T-Bills. In addition to these findings, it was also noted that South African and Kenyan T-Bill yields include a volatility risk premium to compensate investors for the volatility associated with these instruments.

The finding of a significant risk premium in Kenyan and South African T-Bills certainly calls into question the use of these instruments as proxies for the risk-free rate in asset pricing models, and as a benchmark rate in determining the yield curve or pricing long-term bonds. Certainly this result necessitates further research to explicitly examine the usefulness of these instruments as proxies for the risk-free rate and possible explanations for the inclusion of these premia. In so doing, a comparison with long-term government instruments can be conducted to assess whether these instruments include a risk premium.

Despite the success of the CGARCH specification in modelling the T-Bill series in this paper, several studies of the U.S. short-term security have indicated that modelling the interest rate should be taken a step further; such that not only is the volatility persistence of the securities taken into consideration, but also the dependence of volatility on the level of the interest rate (Lanne and Saikonnen, 2003). Models such as mixture autoregressive processes have been employed for this purpose and represent a feasible extension to this work to further examine the nature of the volatility of these important short-term instruments.

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