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Bootstrap causality between inflation uncertainty and output growth uncertainty in selected African countries

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Abstract

The study examines the causal relationship between inflation uncertainty and output growth uncertainty for selected African countries. Asymmetric BEKK GARCH-M model is used to derive measures of uncertainty for inflation and output growth, and bootstrap causality testing approach is used to examine the causal links between them. The findings suggest that Logue and Sweeney (1981) hypothesis and Devereux (1989) hypothesis are supported for Algeria and South Africa; a trade-off hypothesis of Taylor (1981) and Fuhrer (1997) is supported for Gabon, Libya and Tunisia; no causality whatsoever is found for Congo Republic and Nigeria, while for Libya and Tunisia, inflation uncertainty does not affect output growth uncertainty. Further studies are needed to shed more light on the relationship between these important macroeconomic variables for African countries which are still under-researched.

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1. Introduction

Achieving the stability of macroeconomic aggregates such as inflation and output growth is one of the main objectives of monetary authorities. According to Ball (1999), an appropriate monetary policy produces a low inflation but also ensures the stability of inflation and output growth. However, as Taylor (1981) and Fuhrer (1997) claim, the stability of those two aggregates cannot be achieved at the same time, achieving stability of inflation will come at the expense of accepting high volatile (uncertain) output growth and vice-versa, achieving output growth stability will come at the expense of a high volatile inflation, which is the so-called trade-off hypothesis between inflation volatility (uncertainty) and output growth volatility (uncertainty). Logue and Sweeney (1981) and Devereux (1989) propose a contradicting view and suggest a positive relationship between inflation (volatility) uncertainty and output growth uncertainty (volatility).

Logue and Sweeney (1981) argue that greater uncertainty in inflation leads to greater uncertainty in investment marketing decisions, hence greater uncertainty in production. According to them, in high inflationary economies, producers receive distorted signals concerning demand for their goods, creating uncertainty of the demand of their goods and causing instability in production decisions. The change in investments becomes uncertain leading to real growth uncertainty. Logue and Sweeney (1981) therefore support a positive impact of inflation uncertainty on output growth uncertainty. Devereux (1989) in his model also supports the existence of a positive relationship between inflation volatility (uncertainty) and output growth volatility (uncertainty) but suggests that it is rather output growth volatility (uncertainty) which affects inflation volatility (uncertainty) and not the other way around. According to him therefore, an increase in output growth volatility (uncertainty) precedes an increase in inflation volatility (uncertainty).

While a number of empirical studies exist in this area (see for instance, Karanasos and Kim 2005, Fountas et al. 2006, Conrad and Karanasos 2008, and Paloviita and Viren 2012), similar studies remain scarce for African economies. In fact, to the best of my knowledge only one study exists on African countries (see Onyukwu et al. 2011). This study therefore contributes to the literature by examining the relationship between inflation uncertainty and output growth uncertainty for seven selected African countries.

In this study, a two-step approach, where uncertainty measures are first derived and then causal links are examined, is preferred to a simultaneous approach. As Fountas et al. (2004) point out, the causal links the simultaneous approach permits to examine are only contemporaneous, which according to Grier and Perry (1998) is misleading since such links take time to materialize.

The novelty of this study is the use of asymmetric BEKK GARCH-M model advanced by Grier et al. (2004) to derive the measures of inflation uncertainty and output growth uncertainty. To examine the relationship between them, bootstrap causality testing approach initiated by Hacker and Hatemi-J (2012) is used.

The rest of the chapter is organized as follows: Section 2 highlights the methodology and data used. Section 3 presents the empirical results and section 4 gives the concluding remarks.

2. Methodology and Data

As pointed out in section one, a two-step approach is used in this study. Uncertainty measures of inflation and output growth are first derived and then causal links between inflation uncertainty and output growth uncertainty are examined. To derive the measures of inflation uncertainty and output growth uncertainty, the study follows Grier et al. (2004) and uses an asymmetric multivariate GARCH model, asymmetric BEKK GARCH-M model, where diagonality and symmetry of the conditional variance-covariance matrix are tested instead of being imposed[1].

Prior to estimating a GARCH model, it is important to estimate an appropriate conditional mean equation. Following Grier et al. (2004), the conditional means of inflation (π_t) and output growth (y_t) are in form of VARMA (Vector Autoregressive Moving Average) GARCH-M model, where the conditional standard deviations of output growth and inflation are included as explanatory variables in each conditional mean equation. The specification of the conditional means of inflation (π_t) and output growth (y_t) is presented in equation (1) and the conditional variance-covariance matrix in equation (2), where, H_t is the conditional variance-covariance matrix, $h_{y,t}$ is the conditional variance of output growth, $h_{\pi,t}$ is the conditional variance of inflation, $h_{y\pi,t}$ & $h_{\pi y,t}$ are the conditional covariances between inflation and output growth, ε_t is the vector of error terms, μ is the matrix of constant terms, Γ_i is the matrix of Autoregressive coefficients, Ψ is the matrix of in-mean coefficients, Θ_j is the matrix of Moving Average coefficients, C is the matrix of constant terms, A is the matrix of ARCH terms, B is the matrix of GARCH terms, and D is the matrix of asymmetric coefficients. The BEKK model becomes symmetric if $\delta_{ij} = 0$.

From the asymmetric BEKK GARCH-M model, uncertainty measures of inflation and output growth are to be captured by the estimated conditional variances of the variables, which is just the variance of the one step ahead forecasting error.

$$Y_t = \mu + \sum_{i=1}^{p} \Gamma_i Y_{t-i} + \Psi\sqrt{h_t} + \sum_{j=1}^{q} \Theta_j \varepsilon_{t-j} + \varepsilon_t, \qquad (1)$$

$$\varepsilon_t \sim (0, H_t)$$

$$H_t = \begin{bmatrix} h_{y,t} & h_{\pi y,t} \\ h_{y\pi,t} & h_{\pi,t} \end{bmatrix}$$

$$Y_t = \begin{bmatrix} y_t \\ \pi_t \end{bmatrix}; \varepsilon_t = \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{\pi,t} \end{bmatrix}; \sqrt{h_t} = \begin{bmatrix} \sqrt{h_{y,t}} \\ \sqrt{h_{\pi,t}} \end{bmatrix}; \mu = \begin{bmatrix} \mu_y \\ \mu_\pi \end{bmatrix}; \Gamma_i = \begin{bmatrix} \Gamma_{11}^{(i)} & \Gamma_{12}^{(i)} \\ \Gamma_{21}^{(i)} & \Gamma_{22}^{(i)} \end{bmatrix};$$

$$\Psi = \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix}; \Theta_j = \begin{bmatrix} \theta_{11}^{(j)} & \theta_{12}^{(j)} \\ \theta_{21}^{(j)} & \theta_{22}^{(j)} \end{bmatrix}$$

[1] According to Grier et al. (2004), imposing diagonality and symmetry can lead to misspecification in the conditional variance-covariance matrix, hence wrong measures of uncertainty.

The conditional variance-covariance matrix of an asymmetric BEKK model is written as

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + B'H_{t-1}B + D'\omega_{t-1}\omega_{t-1}'D \tag{2}$$

where,

$$C = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}; A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}; B = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}; D = \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \end{bmatrix}; \omega = \begin{bmatrix} \omega_{y,t} \\ \omega_{\pi,t} \end{bmatrix}$$

After deriving the measures of inflation uncertainty and output growth uncertainty, to account for the problems of non-normality in error terms and the presence of ARCH effects, bootstrap causality testing procedure proposed by Hacker and Hatemi-J (2012) is used to investigate the causal links between inflation uncertainty and output growth uncertainty.
Examining the causal link between two variables[2] y_t and x_t in Granger's sense, involves estimating a *VAR (k)* model which can be specified in a matrix form as follows:

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \sum_{i=1}^{k} \begin{bmatrix} \alpha_{11,i} & \alpha_{12,i} \\ \alpha_{21,i} & \alpha_{22,i} \end{bmatrix} \begin{bmatrix} y_{t-i} \\ x_{t-i} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix} \tag{3}$$

Equation (3) can also be written as:

$$z_t = C + A_1 z_{t-1} + A_2 z_{t-2} + ... + A_k z_{t-k} + \varepsilon_t \tag{4}$$

where $z_t = \begin{bmatrix} y_t \\ x_t \end{bmatrix}, C = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix}$, $[A_1 \quad A_2 \quad ... \quad A_k] = \sum_{i=1}^{k} \begin{bmatrix} \alpha_{11,i} & \alpha_{12,i} \\ \alpha_{21,i} & \alpha_{22,i} \end{bmatrix}$, $\varepsilon_t = \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}$

To test for Granger causality, restrictions are put on *A* coefficients, depending on which direction of causality one is interested in. If for instance, we want to test whether variable x_t Granger-causes variable y_t, we can set the null hypothesis as follows:

$$H0: \alpha_{12,1} = \alpha_{12,2} = ... = \alpha_{12,k} = 0 \tag{5}$$

If this null hypothesis is rejected and the sign of the sum of the estimated causal coefficients is positive (negative), that is, $\sum_{i=1}^{k} \alpha_{12,i} > 0\ (< 0)$, it would imply that an increase in x_t leads to an increase (decrease) in y_t.

However, as Sims, Stock and Watson (1990) pointed out, the coefficients restrictions in expression 5, would be biased in case the variables y_t and x_t are integrated, since the test statistic would not follow the standard asymptotic distribution. To solve this problem, Toda and

[2] In this study, y_t and x_t are inflation uncertainty and output growth uncertainty

Yamamoto (1995) propose to use an augmented VAR model, that is, $VAR(k+d)$ where d is the augmented lag, which is zero (0) if the variables are stationary and one (1) if the variables are integrated of order 1.

The augmented VAR model, $VAR(k+d)$ would be:

$$z_t = C + A_1 z_{t-1} + A_2 z_{t-2} + \ldots + A_k z_{t-k} + A_{k+d} z_{t-(k+d)} + \varepsilon_t \qquad (6)$$

To test for causality in this setting, restrictions are put on the first k coefficients only, ignoring the extra d lags.
The augmented VAR model can also be written as:

$$Z = \Gamma \varpi + \mu \qquad (7)$$

where $Z = \begin{bmatrix} z_1 & z_2 & \ldots & z_T \end{bmatrix}$; $\varpi_t = \begin{bmatrix} 1 \\ z_t \\ z_{t-1} \\ \vdots \\ z_{t-(k+d-1)} \end{bmatrix}$; $\varpi = [\varpi_0, \varpi_1, \ldots, \varpi_{T-1}]$ $\Gamma = [C, A_1, A_2, \ldots., A_k, A_{k+d}]$ and

$\mu = [\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_T]$
The modified Wald Statistic proposed by Toda and Yamamoto (1995) for the null hypothesis of no causality is as follows:

$$MWALD = (\mathfrak{M}\hat{\lambda})' [\mathfrak{M}(\varpi'\varpi)^{-1} \otimes \Psi_E)\mathfrak{M}']^{-1} (\mathfrak{M}\hat{\lambda}) \sim \chi_k^2 \qquad (8),$$

where $\mathfrak{M}$ is an indicator function which serves to identify restrictions under the null hypothesis; $\hat{\lambda} = vec(\Gamma)$; $\otimes$ is the Kronecker product; and Ψ_E is the estimated residuals variance-covariance matrix from equation (7) before imposing restrictions of the null hypothesis.

According to Hacker and Hatemi-J (2012), in case the error terms are normally distributed and ARCH effects are not present, the Modified Wald test statistic in expression (8) follows a chi-square distribution with k degrees of freedom. However, they argue that when error terms are not normally distributed and ARCH effects are present, the Wald test statistic does no longer follow the standard asymptotic distribution leading to an over-rejection of the null hypothesis of no causality. In this case, the solution they propose is bootstrap causality testing which give precise critical values.
The aim of bootstrapping is to approximate the distribution of the Wald test statistic which has been biased by non-normality in error terms and the presence of ARCH effects, by using data resampling procedure.

According to Hacker and Hatemi-J (2012), bootstrap causality testing is conducted in the following steps:

Step 1: Estimating equation (7)
Step 2: Next step consists of simulating bootstrapped residuals μ^* via resampling with replacement, $\mu^* = \left\{\mu_1^*, \mu_2^*, ..., \mu_n^*\right\}, \mu_i^* \in \mu \ \forall i, i = 1, ..., n,$ where n is the bootstrap sample

Step 3: Y^* is generated using the coefficients estimated in step 1, that is, $Z^* = \hat{\Gamma}\varpi + \mu^*$, where $\hat{\Gamma} = (\varpi'\varpi)^{-1}\varpi' X$, ϖ is the original data and μ^* are bootstrapped residuals which are original residuals adjusted with leverages in such a way that non-normality and ARCH effects are corrected.

Step 4: Estimate the vector parameter Γ^* using the generated Y^* in step 3.

Step 5: Using the bootstrapped data, the Wald test statistic is computed, that is, $WALD^* = (\mathfrak{M}\hat{\lambda})'[\mathfrak{M}(\varpi^{*}{}'\varpi^*)^{-1} \otimes \Psi^*{}_E)\mathfrak{M}']^{-1}(\mathfrak{M}\hat{\lambda})$

Step 6: Steps 2 to 5 are repeated N times and the estimated Wald statistics $WALD^*$ are ranked so as to create its bootstrap distribution.

Step 7: The bootstrap critical values at $\alpha\%$ level of significance (c_α^*) are obtained by taking the $(\alpha)^{th}$ upper quantile of the distribution of bootstrapped Wald test statistics, $WALD^*$

Step 8: In the final step, the Wald statistic is computed using the original data. The null hypothesis of no Granger causality is rejected if the Wald statistic WALD is greater than the bootstrap critical value (c_α^*) at $\alpha\%$ level of significance

Since GARCH models are more appropriate with high frequency data, monthly data on inflation and output growth are used in this study for seven selected African countries namely, Algeria, Congo Republic, Gabon, Libya, Nigeria, South Africa and Tunisia[3]. Because of unavailability of high frequency data on GDP, this study adopts crude petroleum production index as a proxy for output for Algeria, Libya, Republic of Congo, Gabon and Nigeria since they are oil-based economies (oil sector in these countries is the major contributor to GDP and export revenues). For Tunisia and South Africa, industrial and manufacturing production index is respectively used as proxy for output since the manufacturing and industrial sectors of those countries are well developed.

Table 1 summarizes the data description for each selected country involved in this analysis. Data used are from International Financial Statistics of the IMF, online database. Inflation rate is computed as the monthly difference of the logarithm of CPI, $\pi_t = [\log(CPI_t / CPI_{t-1})]*100$ and output growth is computed as the monthly difference of the logarithm of the production index (Y_t), $y_t = [\log(Y_t / Y_{t-1})]*100$.

[3] The choice of these countries is based to availability of high frequency data for the proxy of output which could better capture the country's economic activity.

Table 1: Data Description for Selected African Countries

Country	Price Data	Output Data	Sample size	Number of Obs.
Algeria	CPI	CPPI	1974:02-2012:05	460
Congo Rep.	CPI	CPPI	1998:02-2006:07	102
Gabon	CPI	CPPI	1978:02-2012:02	409
Libya	CPI	CPPI	2001:02-2011:06	125
Nigeria	CPI	CPPI	1971:02-2008:04	447
South Africa	CPI	MfPI	1961:02-2012:03	614
Tunisia	CPI	IPI	1987:07-2012:02	296

Note: CPI stands for Consumer Price Index, CPPI, Crude Petroleum Production Index, IPI, Industrial Production Index, and MfPI, Manufactured Production Index.

3. Empirical Results and Discussion

Prior to estimating our GARCH model, unit root tests and ARCH tests are conducted. Unit root tests results are reported in Table 2. They indicate that both tests used, an endogenous two-break unit root test of Lee-Strazicich (2003) and a non-parametric unit root test of Breitung (2002), strongly reject the null hypothesis of a unit root in inflation and output growth series for all the selected countries. Inflation and output growth series are hence integrated of order 0, I (0) and this implies that there is no need to difference them when estimating the Mean equations.

In addition, Ljung-Box (1978) test in Appendix 1 rejects the null hypothesis of no serial correlation in both the series and squared series, while univariate and multivariate LM-ARCH tests (see Appendices 1 and 2) reject the null hypothesis of no ARCH effects, implying that the variances of inflation and output growth are not constant but time-varying. We proceed therefore to estimate our asymmetric BEKK GARCH-M model since the presence of ARCH effects in the data is confirmed. Table 3 presents the estimation results for South Africa[4].

Diagnostic tests on the estimated asymmetric BEKK GARCH-M model, Ljung-Box test and McLeod-Li test (see Table 3**,** panel C), are used to check for the adequacy of the estimated model. They indicate that the conditional mean and conditional variance-covariance equations are well specified. In addition, coefficient restriction tests[5] in Table 3 (panel C) suggest that none of the coefficients in the mean equation and in the conditional variance-covariance matrix are redundant. This confirms that VARMA model adopted for the specification of the mean equation captures adequately the dynamics of inflation and output growth and asymmetric BEKK GARCH-M model used captures well the dynamics of the conditional variances of the variables.

[4] For convenience, we present only the estimation results for South Africa. For the rest of the countries, the results are available upon request.

[5] Coefficients restriction tests reject the hypotheses of diagonality and symmetry in the conditional variance-covariance matrix, imposing them would have hence led to a misspecification problem.

Table 2: Unit Root Tests Results

Panel A: Unit Root Tests for Inflation					
COUNTRY	Lee-Strazicich Unit Root Test			Breitung Test	
	τ Stat	BREAKS		B(n)/n	C.V (5%)
Algeria	-13.95***(3)	1989m7	1995m2	0.00152[0.000]	0.01039
Congo Rep.	-11.26***(0)	2000m2	2000m11	0.00084[0.000]	0.01004
Gabon	-10.29***(3)	1983m7	1988m2	0.00132[0.000]	0.01030
Libya	-11.04***(0)	2008m4	2009m5	0.00754[0.035]	0.01004
Nigeria	-9.96***(5)	1988m11	1995m8	0.00132[0.000]	0.01037
South Africa	-13.20***(2)	1985m12	1998m7	0.00628[0.009]	0.01046
Tunisia	-12.82***(0)	1990m12	2005m3	0.00700[0.025]	0.01011
Panel B: Unit Root Tests for Output Growth					
COUNTRY	Lee-Strazicich Unit Root Test			Breitung Test	
	τ Stat	BREAKS		B(n)/n	C.V (5%)
Algeria	-13.70***(5)	1998m2	2002m3	0.00012[0.000]	0.01039
Congo Rep.	-13.82***(0)	2000m5	2001m6	0.00007[0.000]	0.01004
Gabon	-13.51***(10)	1989m9	1998m3	0.00008[0.000]	0.01030
Libya	-8.91***(0)	2007m6	2010m7	0.00700[0.094]	0.01004
Nigeria	-14.39***(5)	1983m6	1987m5	0.00002[0.000]	0.01037
South Africa	-15.83***(7)	1968m6	1976m11	0.00052[0.000]	0.01046
Tunisia	-17.36***(0)	1993m3	1995m9	0.00010[0.000]	0.01011

Note: Lee-Strazicich Test was performed using WinRATS Pro 8.1 while Breitung test was performed using EasyReg software. Between parentheses (.) are the optimal lags used in L-S test, selected using the usual criteria and brackets [.] are the p-values for Breitung test. For L-S Test, 1% C.V is -5.823; 5% C.V is -5.286 and 10% C.V is -4.989 for the model allowing for a shift in intercept and change in trend slope. P-values reported in brackets [.] for Breitung Test are based on 1000 simulations.

Since our estimated asymmetric BEKK GACRH-M model is well specified for all the countries, we generate inflation uncertainty and output growth uncertainty captured by the conditional standard deviation of inflation and output growth respectively. Appendix 4 presents the estimated inflation uncertainty and output growth uncertainty for South Africa[6].

After getting the measures of uncertainty for inflation and output growth, we examine the causal links between them. However, prior to that, diagnostic tests, normality and ARCH effects tests are conducted, on the estimated VAR model of inflation uncertainty and output growth uncertainty.

The diagnostic tests results reported in Appendix 3 indicate that indeed error terms are not normally distributed and ARCH effects are present, which causes an inferential problem according to Hacker and Hatemi-J (2012). In this case, the Wald test statistic of no causality does no longer follow the standard asymptotic distribution and that, according to Hacker and Hatemi-J (2012) leads to over-rejection of the null hypothesis of no causality. Bootstrap causality testing is the solution proposed by the authors giving precise critical values. Bootstrap causality tests results between inflation uncertainty ($h_{\pi\pi}$) and output growth uncertainty (h_{yy}) for the selected African countries are presented in Table 4. A GAUSS code written by Hacker and Hatemi-J (2011) is used and 10000 simulations are employed to simulate critical values.

[6] For the rest of the countries, Figures of the estimated uncertainty measures are available upon request.

Table 3: Asymmetric BEKK GARCH-M Model for South Africa

Panel A: Conditional Mean Equations

$$Y_t = \mu + \sum_{i=1}^{p} \Gamma_i Y_{t-i} + \Psi\sqrt{h_t} + \sum_{j=1}^{q} \Theta_j \varepsilon_{t-j} + \varepsilon_t, \text{ where } \varepsilon_t \sim (0, H_t)$$

$$\mu = \begin{bmatrix} \begin{matrix} 2.2727 \\ (0.000) \end{matrix} \\ \begin{matrix} 0.1037 \\ (0.000) \end{matrix} \end{bmatrix}; \Gamma_1 = \begin{bmatrix} \begin{matrix} \text{-}1.0031 \\ (0.000) \end{matrix} & \begin{matrix} 8.5938 \\ (0.000) \end{matrix} \\ \begin{matrix} \text{-}0.0239 \\ (0.000) \end{matrix} & \begin{matrix} 0.7070 \\ (0.000) \end{matrix} \end{bmatrix}; \Gamma_2 = \begin{bmatrix} \begin{matrix} \text{-}0.6469 \\ (0.000) \end{matrix} & \begin{matrix} \text{-}10.2235 \\ (0.000) \end{matrix} \\ \begin{matrix} 0.0028 \\ (0.000) \end{matrix} & \begin{matrix} 0.2756 \\ (0.000) \end{matrix} \end{bmatrix};$$

$$\Psi = \begin{bmatrix} \begin{matrix} \text{-}0.4359 \\ (0.000) \end{matrix} & \begin{matrix} 0.8442 \\ (0.059) \end{matrix} \\ \begin{matrix} \text{-}0.0430 \\ (0.000) \end{matrix} & \begin{matrix} 0.0115 \\ (0.030) \end{matrix} \end{bmatrix}; \Theta_1 = \begin{bmatrix} \begin{matrix} 0.4436 \\ (0.000) \end{matrix} & \begin{matrix} \text{-}9.0136 \\ (0.000) \end{matrix} \\ \begin{matrix} 0.0453 \\ (0.000) \end{matrix} & \begin{matrix} \text{-}0.6281 \\ (0.000) \end{matrix} \end{bmatrix}; \Theta_2 = \begin{bmatrix} \begin{matrix} 0.0154 \\ (0.613) \end{matrix} & \begin{matrix} 9.1137 \\ (0.000) \end{matrix} \\ \begin{matrix} \text{-}0.0301 \\ (0.000) \end{matrix} & \begin{matrix} \text{-}0.2759 \\ (0.000) \end{matrix} \end{bmatrix}$$

Panel B: Conditional Variance-Covariance

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\omega_{t-1}\omega'_{t-1}D$$

$$C = \begin{bmatrix} \begin{matrix} 1.5106 \\ (0.000) \end{matrix} & 0 \\ \begin{matrix} 0.0116 \\ (0.453) \end{matrix} & \begin{matrix} \text{-}0.00003 \\ (0.999) \end{matrix} \end{bmatrix}; A = \begin{bmatrix} \begin{matrix} 0.2521 \\ (0.000) \end{matrix} & \begin{matrix} \text{-}0.0193 \\ (0.0015) \end{matrix} \\ \begin{matrix} \text{-}0.2072 \\ (0.457) \end{matrix} & \begin{matrix} 0.2276 \\ (0.000) \end{matrix} \end{bmatrix}; B = \begin{bmatrix} \begin{matrix} \text{-}0.5387 \\ (0.000) \end{matrix} & \begin{matrix} 0.0239 \\ (0.169) \end{matrix} \\ \begin{matrix} 0.0039 \\ (0.986) \end{matrix} & \begin{matrix} 0.9487 \\ (0.000) \end{matrix} \end{bmatrix}; \ \mathrm{D} = \begin{bmatrix} \begin{matrix} 0.3674 \\ (0.000) \end{matrix} & \begin{matrix} 0.0149 \\ (0.143) \end{matrix} \\ \begin{matrix} 1.5841 \\ (0.000) \end{matrix} & \begin{matrix} 0.2650 \\ (0.000) \end{matrix} \end{bmatrix}$$

$$\textit{Diagonal VARMA}: [H0: \ \Gamma_{12}^{i} = \Gamma_{21}^{i} = \theta_{12}^{i} = \theta_{21}^{i} = 0, i = 1, 2, \ \ \chi^2(8) = 207659.3(0.000)]$$

$$\textit{No GARCH}: [H0: \ \alpha_{ij} = \beta_{ij} = \delta_{ij} = 0, \forall i, j; \ \ \chi^2(12) = 219448.3(0.000)]$$

$$\textit{No GARCH} - M: [H0: \ \psi_{ij} = 0, \forall i, j; \ \ \chi^2(4) = 2236.9(0.000)]$$

$$\textit{No ASYMMETRY}: [H0: \ \delta_{ij} = 0, \forall i, j; \ \ \chi^2(4) = 856.3(0.000)]$$

$$\textit{Diagonal GARCH}: [H0: \ \alpha_{12} = \alpha_{21} = \beta_{12} = \beta_{21} = \delta_{12} = \delta_{21} = 0, \forall i, j; \ \ \chi^2(6) = 81.1(0.000)]$$

Panel C: Diagnostic Tests

	Ljung-Box Q(5)	**McLeod-Li(5)**	**Ljung-Box Q(10)**	**McLeod-Li(10)**
$z_{y,t}$	6.4460 (0.265)	1.117 (0.952)	13.0139 (0.222)	6.1748 (0.800)
$z_{\pi,t}$	7.0156 (0.219)	2.2824 (0.808)	17.1519 (0.071)	3.7045 (0.959)

Source: Results from our estimations using WinRATS Pro 8.1. Between parentheses (.) are the p-values.

Bootstrap causality tests results suggest positive bidirectional causality between inflation uncertainty and output growth uncertainty for Algeria and South Africa, implying that an increase in inflation volatility (uncertainty) would lead to output growth (volatility) uncertainty and vice versa, supporting Logue and Sweeney (1981) hypothesis and Devereux (1989) hypothesis. Instability in either of the two variables would lead to instability in the other but also policies stabilizing one of them could also stabilize the other.

For Gabon, Libya and Tunisia, the findings support a trade-off hypothesis of Taylor (1981) and Fuhrer (1997) in one direction although the evidence is weak for Gabon and Tunisia (at 4 lags only). A decrease in output growth uncertainty (volatility) would lead to an increase in inflation uncertainty (volatility) and not the other way around. This implies that stabilizing output growth in Gabon, Libya and Tunisia would be achieved at the expense of accepting high inflation instability.

Table 4: Bootstrap Causality between inflation uncertainty and output growth uncertainty

Countries	H0: $h_{\pi\pi}$ does not Granger-cause h_{yy}			H0: h_{yy} does not Granger-cause $h_{\pi\pi}$		
	Test Value			Test Value		
	4 lags	8 lags	10 lags	4 lags	8 lags	10 lags
Algeria	7.531*[+]	8.901[+]	14.703[+]	151.26***[+]	146.44***[+]	148.3***[+]
Congo R.	0.194[-]	3.816[+]	3.656[+]	0.262[-]	11.20[-]	14.69[+]
Gabon	39.576**[+]	51.594**[+]	52.439**[-]	9.220*[-]	11.187[-]	11.508[-]
Libya	0.308[-]	0.434[-]	-	7.659**[-]	12.515**[-]	-
Nigeria	2.124[-]	2.838[-]	6.344[+]	0.857[-]	1.769[-]	2.257[-]
S.A	122.11***[+]	184.33***[+]	195.6***[+]	10.31**[+]	21.99***[+]	26.94***[+]
Tunisia	0.306[-]	0.567[-]	0.718[-]	7.072*[-]	7.681[-]	7.607[-]

Bootstrap Critical Values for H0: $h_{\pi\pi}$ does not Granger-cause h_{yy}

Countries	4 lags			8 lags			10 lags		
	1% CV	5% CV	10% CV	1% CV	5% CV	10% CV	1% CV	5% CV	10% CV
Algeria	42.16	11.70	6.73	98.45	25.17	14.21	117.48	30.02	17.77
Congo	82.47	24.10	10.20	150.06	36.97	20.56	103.24	49.21	25.96
Gabon	48.50	12.87	7.80	94.36	26.15	16.25	106.14	31.91	19.44
Libya	10.21	4.12	2.57	19.62	7.63	4.77	-	-	-
Nigeria	27.51	13.55	8.88	40.58	21.26	15.58	47.54	25.88	18.99
S.A	9.98	6.22	4.66	14.88	10.04	8.00	18.96	13.09	10.89
Tunisia	75.78	14.10	7.34	148.77	33.25	16.90	180.13	45.46	22.36

Bootstrap Critical Values for H0: h_{yy} does not Granger-cause $h_{\pi\pi}$

Countries	4 lags			8 lags			10 lags		
	1% CV	5% CV	10% CV	1% CV	5% CV	10% CV	1% CV	5% CV	10% CV
Algeria	42.31	11.76	7.54	88.78	21.64	14.30	94.38	24.74	16.81
Congo	73.04	24.70	10.66	295.44	43.94	22.03	53.89	29.06	20.93
Gabon	41.56	12.33	7.63	95.73	25.27	15.87	112.11	29.97	19.38
Libya	14.81	4.81	2.55	21.12	7.88	4.86	-	-	-
Nigeria	25.53	11.79	8.07	40.29	20.91	15.60	46.60	24.27	18.19
S.A	10.92	6.31	4.61	16.33	10.34	8.09	20.37	13.78	10.91
Tunisia	85.70	16.36	6.74	133.07	37.93	18.29	177.13	45.92	23.31

Notes: Bootstrap causality tests were performed using a GAUSS code written by Hacker and Hatemi-J (2011), available in the statistical software components archive. Bootstrap critical values are obtained using 10000 simulations. Between [.] is the sign of the sum of the estimated causal coefficients; *, ** and *** denotes rejection of the null hypothesis at 10%, 5% and 1% respectively. S.A stands for South Africa. For Libya, a lag length of 10 was too big to handle.

For Gabon, the results provide mixed evidence concerning the impact of inflation uncertainty on output growth uncertainty, with a positive causal impact at 4 lags and 8 lags, and negative at 10 lags. For Congo Republic, Libya, Nigeria and Tunisia, inflation uncertainty does not Granger-cause output growth uncertainty and output growth uncertainty does not affect inflation uncertainty for Congo Republic and Nigeria.

It should be noted that our findings on the link between inflation uncertainty and output growth uncertainty for Nigeria suggest that there is no causal link whatsoever between those variables, contradicting with Onyukwu et al. (2011) who suggested a trade-off between inflation uncertainty and output growth uncertainty in short-run.

4. Concluding Remarks

The objective of this study was to examine the causal links between inflation uncertainty and output growth uncertainty for seven selected African countries, namely Algeria, Congo Republic, Gabon, Libya, Nigeria, South Africa and Tunisia. To derive measures of inflation uncertainty and output growth uncertainty, asymmetric BEKK GARCH-M model is used following Grier et al. (2004). The advantage of the methodology is that it allows testing for diagonality and symmetry in the conditional variance-covariance matrix instead of imposing them. To examine the causal relationship between inflation uncertainty and output growth uncertainty, the study follows Hacker and Hatemi-J (2012) and uses bootstrap causality tests to account for non-normality in error terms and the presence of ARCH effects in the data. The findings support Logue and Sweeney (1981) and Devereux (1989) hypotheses for Algeria and South Africa. For Gabon, Libya and Tunisia, the trade-off hypothesis of Taylor (1981) and Fuhrer (1997) was supported. No causality whatsoever is found for Congo Republic and Nigeria, while for Libya and Tunisia, inflation uncertainty does not affect output growth uncertainty. Further studies are needed to shed more light on the relationship between these important macroeconomic variables for African countries which are still under-researched.

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Appendices

Appendix 1: Univariate Serial Correlation and ARCH tests Results

Panel A: Univariate Serial Correlation and ARCH test for Inflation

COUNTRIES	Q(10)	Q(20)	Q^2(10)	Q^2(20)	ARCH (20)
Algeria	24.82 (0.005)	181.3 (0.000)	66.33 (0.000)	200.7 (0.000)	7.70 (0.000)
Congo Rep.	10.71 (0.379)	20.98 (0.397)	4.45 (0.924)	9.36 (0.978)	2.51 (0.003)
Gabon	34.00 (0.000)	48.90 (0.000)	66.40 (0.000)	67.18 (0.000)	3.65 (0.000)
Libya	13.80 (0.182)	24.20 (0.233)	1.38 (0.999)	3.80 (0.999)	0.19 (0.999)
Nigeria	128.4 (0.000)	217.4 (0.000)	116.7 (0.000)	146.0 (0.000)	4.77 (0.000)
South Africa	465.9 (0.000)	894.0 (0.000)	125.9 (0.000)	360.0 (0.000)	8.30 (0.000)
Tunisia	43.78 (0.000)	143.9 (0.000)	15.60 (0.11)	167.5 (0.000)	12.18 (0.000)

Panel B: Univariate Serial Correlation and ARCH Effects test for Output Growth

COUNTRIES	Q(10)	Q(20)	Q^2(10)	Q^2(20)	ARCH (20)
Algeria	122.5 (0.000)	364.6 (0.000)	50.65 (0.000)	54.14 (0.000)	2.55 (0.000)
Congo Rep.	26.40 (0.003)	37.51 (0.010)	23.38 (0.009)	24.82 (0.208)	1.77 (0.044)
Gabon	115.8 (0.000)	287.5 (0.000)	46.73 (0.000)	56.07 (0.000)	1.68 (0.033)
Libya	29.87 (0.000)	31.79 (0.045)	4.44 (0.92)	4.45 (0.999)	0.63 (0.877)
Nigeria	55.34 (0.000)	136.3 (0.000)	416.2 (0.000)	606.0 (0.000)	11.94 (0.000)
South Africa	369.8 (0.000)	568.6 (0.000)	74.81 (0.000)	99.71 (0.000)	4.29 (0.000)
Tunisia	31.70 (0.000)	44.67 (0.001)	28.76 (0.001)	29.06 (0.086)	2.39 (0.009)*

Notes: Tests performed using OxMetrics 6.30. (*) indicates that ARCH test for Tunisia is up to 10 lags. Between parentheses (.) are the P-values.

Appendix 2: Multivariate ARCH Effects test

COUNTRIES	LM (4)	LM(8)	LM(12)
Algeria	377.75[0.000]	216.73[0.000]	138.31[0.000]
Congo Rep.	197.17[0.000]	104.09[0.007]	63.11[0.003]
Gabon	258.04[0.000]	284.01[0.000]	318.19[0.000]
Libya	3096.8[0.000]	2249.7[0.000]	1989.4[0.000]
Nigeria	507.69[0.000]	402.98[0.000]	282.48[0.000]
South Africa	495.93[0.000]	316.84[0.000]	250.38[0.000]
Tunisia	572.58[0.000]	254.14[0.000]	93.74[0.000]

Notes: Test was performed using WinRATS Pro 8.1. Between brackets [.] are the P-values for the test

Appendix 3: Multivariate Diagnostic tests on the VAR model of inflation uncertainty and output growth uncertainty

	Multivariate Normality Test			Multivariate ARCH-LM Test		
	VAR (4)	**VAR (8)**	**VAR(10)**	**VAR (4)**	**VAR (8)**	**VAR(10)**
Algeria	2434348.1***	2365433.1***	2262614.3***	128.68***	136.24***	123.79***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Congo	46926.50***	24915.7***	22290.6***	37.75	58.55*	65.12**
	(0.000)	(0.000)	(0.000)	(0.769)	(0.084)	(0.026)
Gabon	189406.1***	180945.8***	167511.0***	389.96***	386.15***	383.81***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Libya	57077.8***	57383.9***	-	203.31***	75.38***	-
	(0.000)	(0.000)		(0.000)	(0.000)	
Nigeria	138448.5***	135579.3***	161495.0***	109.34***	30.19	27.75
	(0.000)	(0.000)	(0.000)	(0.000)	(0.955)	(0.979)
S.A	65523.2***	70427.9***	71305.7***	71.98***	44.62	45.88
	(0.000)	(0.000)	(0.000)	(0.006)	(0.487)	(0.435)
Tunisia	728982.0***	591235.5***	-	133.64***	131.40***	-
	(0.000)	(0.000)		(0.000)	(0.000)	

Notes: The test results are from JMulTi 4.23 software; multivariate Normality test used is of Doornik & Hansen (1994, 2008) and for multivariate ARCH-LM test, Doornik & Hendry (1997) test is used, they both follow a chi-square distribution and 5 lags are used. Under the chi-square test statistics, are the p-values in parentheses. *, ** and *** indicate the rejection of the null hypothesis at 10%, 5% and 1% respectively.

Appendix 4: Inflation Uncertainty and Output Growth Uncertainty for South Africa