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Inflations and its uncertainty in Some ECOWAS member states: Transfer Entropy Approach

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This study examines the information flow between inflation and inflation uncertainty (IU) and intrastate inflationary trend among some ECOWAS member states. IU is measured using GARCH models and stochastic volatility model (SV). Transfer entropy was adopted to quantify the extent of information flow. The result showed information flow exists from inflation to the GARCH measure of IU. On the reverse flow from inflation uncertainty to inflation, there is no information flow except for Burkina Faso and Gambia which have asymmetric bidirectional flow between inflation and IU. Adopting SV measure for IU, there are no support for causality from inflation to IU for all the member states except Burkina Faso and Cabo Verde. For the reverse flow, causality exists in all the member states. On the pairwise inflation trend of member states, inflation trends are interconnected and that shocks in one country may transmit to others except for Gambia, Cote d'Ivoire and Burkina Faso. Specifically, Guinea, Liberia and Nigeria inflation shocks have the greatest effect on other WAMZ members within the study period, whereas inflation trend in Benin, Niger and Cote d'Ivoire are the most influential among WAEMU states. In conclusion, inflation - IU relationship is sensitive to how IU is measured leading to mixed findings. This study recommends the need for price stability among the ECOWAS member states. Given the interdependence among some members of each bloc of ECOWAS, policy synchronization on price stability could enhance the overall objective of single digit inflation and reduce the welfare effect of inflation uncertainty

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1. Introduction

Economic Community of West African States (ECOWAS) is a group of countries created to promote economic integration among the West African States. Within the

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ECOWAS, there are two economic blocs: The West African Economic and Monetary Union (WAEMU) whose members comprise of Francophone countries, and the West African Monetary Zone (WAMZ) whose goal is to create a common currency-'ECO', among member states who are mostly Anglophone countries. The interest of the two blocs is to strengthen economic integration of the member states. Hence, regional harmonisation of fiscal and monetary policies and ensuring price stability can foster growth among member states.

The role of inflation and its uncertainty (henceforth, IU) has been a key focus due to the welfare effect of inflation. Friedman (1977) presented an argument which postulated that higher inflation gives room for increase in inflation uncertainty (IU) while Ball (1992) provided a macroeconomic model in explaining the causality of inflation and inflation uncertainty, hence, Friedman – Ball hypothesis (FBH). Base on the postulation of FBH, the welfare effect of inflation is twofold. The first is the increase in inflation uncertainty due to increase in inflation. Second, the real output thus declines due to the increased uncertainty about the future inflation. The causal effect of inflation on its uncertainty was revised by Cukierman & Meltzer (1986) [C-M] on the argument that increase in inflation uncertainty translate to increase in inflation. Insufficient evidence exists for the inflation – inflation uncertainty relation among the ECOWAS member states.

An appropriate measure of IU is still a re-occurring debate. The Autoregressive Conditional Heteroscedasticity (ARCH) and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models are among the methods used to estimate the conditional variance ascribed as the measure of IU. However, Bhar & Hamori (2004) and Karanasos & Schurer (2008) noted that Markov Switching model and power ARCH may be superior to GARCH models in estimating inflation uncertainty. Whereas subsequent studies advocated for Seasonal Fractionally Integrated Smooth Transition Autoregressive Asymmetric Power GARCH model (see Balcilar & Ozdemir, 2013; Nasr, Balcilar, Ajmi, Aye, Gupta & Eyden, 2015), More recent studies by Albulescu *et al.* (2015), Barnett, Ftiti & Jawadi (2018) favoured Stochastic modelling of IU.

The second step towards the inflation-inflation uncertainty involves adopting an efficient estimator. The linear VAR (Granger Causality) is common and has a weak point for its inability to capture structural instabilities present in most time series. Granger-causality regressions do not take into account potential parameter instabilities (Chen, Rogoff & Rossi 2008). In addition, Time domain parametric causality test may perform poorly among variables whose relationship is nonlinear (Diks & Fang, 2020). Besides, an argument set is inflation-inflation uncertainty has a time varying relationship, hence, models that capture this nonlinearity are suitable for establishing information flow between inflation and inflation uncertainty.

The objective of this study is to examine the information flow between inflation and its uncertainty among the ECOWAS member states. This study adopt transfer entropy (TE) in examining the information flow between inflation and inflation uncertainty in ECOWAS. The TE is a nonparametric estimator and a good option for modelling causality due to its ability to capture linear and nonlinear relationship in the inflation - inflation uncertainty relation. 'Using transfer entropy widens the possibilities to detect information flows as nonlinear relationships can also be accounted for' (Behrendt *et al.* 2019). Besides, ECOWAS member states are grossly understudied in terms of FBH and C-M hypothesis.

This study contributes to the existing debate in various ways. First, this study adopts information theory in examining inflation-inflation uncertainty due to its usefulness in time series either possessing linear or nonlinear process. Secondly, this study extends the inflation-inflation uncertainty relation to cover more members of ECOWAS. Thirdly, given the lack of consensus on the best method of measuring IU, all the GARCH variants were given a fair chance using a simulation code provided by Peril *et al.* (2020) to determine the best GARCH model to capture inflation uncertainty. To understand if the inflation and IU relations is susceptible to method adopted in measuring IU, this study adopts stochastic volatility model to obtain IU and attempt to compare the best GARCH variant with stochastic estimated IU. Lastly, this study investigated intra inflationary trends among WAMZ and WAEMU (ECOWAS member states) to determine the interdependence via cause and effect approach using information theory.

The rest of the paper is presented as follows. Discussion of existing theoretical and empirical literature is presented in Section 2. The study methodology and data description in Section 3, Empirical findings and discussion are presented in Section 4 and lastly, in Section 5, the study concludes along with policy implication.

2. Literature Review

2.1 Theoretical Literature

Price stability is one of the core mandate of monetary authorities of the member states of ECOWAS. One of the key issues often discussed in the literature is the socioeconomic effect of inflation. Friedman presents an argument in his lecture in 1977 on the welfare effect of inflation. This argument dubbed Friedman hypothesis postulated a positive effect of increasing inflation on future expectation (inflation uncertainty). This argument was formalized by Ball (1992). On the other hand, when economic agents can forecast inflation movement accurately, this will reduce the risk of inflation uncertainty. Hence, the welfare effect of increase in inflation on inflation uncertainty can be predicted and its associated uncertainty will be reduced as opined by Pourgerami & Maskus (1987). An efficient model which performs in forecasting out of sample is quite essential in mitigating the inflation uncertainty. The cost of maintaining the model is quite determined by the ability to reduce inflation uncertainty due to increase in inflation. Either way, Inflation has a link with its uncertainty.

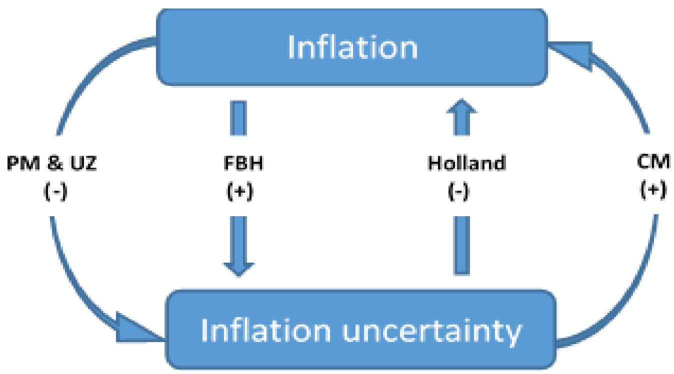

Figure 1: Hypothesis on inflation-inflation uncertainty

As shown in Figure 1, from the reverse perspective, Pourgerami-Maskus (1987) & Ungar-Zilberfarb (1993) [PM & UZ] hypothesis support the opinion that inflation decreases inflation uncertainty. However, inflation uncertainty has been linked to inflation as postulated by the Cukierman and Meltzer (CM) and Holland (1995). In the opinion of Cukierman and Meltzer (1986), increase in inflation uncertainty increases inflation. In contrast to CM, Holland (1995) later postulate a positive impact of inflation uncertainty on inflation. The existence of CM and FBH have been linked to the level of monetary independence. More independent Central Banks tends to have full control in acting to correct inflation from spilling to inflation uncertainty. So, the policy makers are certain to have tougher stance against inflation.

2.2 Empirical Literature

Studies in Africa have shown mixed results for FBH and C-M hypothesis. Most reviewed literature showed FBH hold. Conflicting results hold for C-M hypothesis. Some studies have shown weak support for C-M hypothesis and its existence. When it exists, it depends on the duration. European studies also showed overwhelming support for the FBH. For C-M hypothesis, mixed results exist. The Asian counterpart, also showed support for FBH and C-M hypothesis. The reviewed studies in the developed and emerging economies have shown consistent results for FBH. The C-M hypothesis is inconsistent at country level. The reviewed G7 countries showed consistent and inconsistent support for FBH and C-M hypothesis. Where C-M hypothesis exist, it has a weak statistical significance.

Fernández-Valdovinos and Gerling (2011) examine inflation-inflation uncertainty for countries that form the West African Economic and Monetary Union (WAEMU) from 1994M01 to 2009M12. They estimate the IU, using GARCH model and then examine inflation-inflation uncertainty using linear VAR (Granger causality). The study observed that regional shocks explains a large part of variation in the domestic price level. In addition, cross country correlation of domestic inflation shock is positive. Higher inflation increase inflation uncertainty for WAEMU members (FBH). The study found weak evidence for C-M hypothesis particularly in Benin, Senegal and Togo.

Bouoiyour and Selmi (2014) measure inflation uncertainty using EGARCH and examine changes in the inflation-inflation uncertainty in Egypt. They adopted Taylor approximated nonlinear (within Wavelet framework) causality test to examine inflation-inflation uncertainty in Egypt across various time horizons (frequencies).

The finding showed inflation had a nonlinear causal effect on IU at the highest time horizonand implied the existence of FBH in the longrun. The C-M hypothesis exist in the data having a short time horizon. The study concluded C-M exist in the short run.

Bamanga *et al.* (2016) focused on a member state of ECOWAS (Nigeria). They adopted monthly data from 1960 to 2014. Inflation uncertainty (IU) was modelled using EGARCH. Structural break in the CPI series was modelled using dummy variable on the inflation mean equation as well as the conditional variance equation. The findings from the time domain Granger Causality test indicate inflation causes IU. The reverse causality does not hold, implying absence of C-M hypothesis.

In another study of ECOWAS member state (The Gambia) Mendy and Widodo (2018) adopted monthly data from 1970 - 2017. The proxy for IU was obtained from gjrGARCH model. At first, the findings indicated inconsistency in the relationship between inflation and IU. Subsequently, they adopted a non parametric approach (Toda Yamamoto (1995) Granger causality) to examine the FBH and C-M hypotheses and indicated the existence of FBH and C-M hypothesis for the full sample and post economic reform sample. An exception was for C-M hypothesis which does not hold during the inflation targeting era.

Using monthly data 1920-2012 for South Africa, Nasr *et al.* (2015) adopted Markov Switching Vector Autoregressive (MS-VAR) model on the basis that it can detect the sign and direction of causality between inflation-inflation uncertainty. To capture the nonlinearity of inflation on the IU, they estimated Seasonal Fractionally Integrated Smooth Transition Autoregressive Asymmetric Power GARCH model. The conditional variance reflects the nonlinearity that exists in the inflation and is a suitable measure for IU. At first they compared the linear VAR with MS-VAR. The linear VAR showed inflation does not cause IU nor does IU causes Inflation. MS-VAR findings, which is superior to linear VAR (by model selection criteria) showed the relationship between inflation-inflation uncertainty varies across the four regimes indicating time varying positive relationship between inflation and its uncertainty in favour of Friedman hypothesis over C-M hypothesis.

Alimi (2017) examined inflation-inflation uncertainty in 44 African countries for the period 1986 to 2015 using quantile regression. The study used three measures of inflation uncertainty in other to assess their robustness. Across the five quantiles, the relationship between mean inflation and IU is positive, confirming FBH and C-M hypothesis. Both the mean deviation measure of IU and relative variability of inflation gave a consistent result in establishing FBH and C-M hypothesis. The results of the conditional variance measure of IU showed a higher inflation rate bring about increase in inflation uncertainty [FBH] and higher inflation uncertainty increase inflation (C-M hypothesis).

Fountas *et al.* (2004) examined the relationship between inflation and IU for six European Union for the period 1960Q1-1999Q2. They used EGARCH to estimate conditional variance to proxy IU. Results from the time domain Granger causality indicate inflation increase IU with exception of Germany. On the other hand, the increase in IU lowers inflation in Germany and Netherlands. In reverse sign, increase in IU increase inflation in Italy, Spain and France. Results for the UK indicate inflation positively Granger cause IU and inflation uncertainty Granger cause inflation positively and negatively. The use of EGARCH is premised on the presence of asymmetries in inflation and its uncertainty. The study highlighted that the disadvantage with the use of the simultaneous approach is its inability to capture the lag effect of inflation uncertainty on inflation in model that involves monthly or quarterly data. In other words, for study that adopt monthly data, lag effect of IU on inflation could be essential in estimating inflation uncertainty and the simultaneous approach does not consider testing the role of lag inflation uncertainty. To control for seasonality in the CPI, the estimation of IU was done by including a dummy variable in the mean inflation equation.

Mladenovic (2007) study for Serbia also adopted time domain Granger causality. The study used GARCH to estimate the IU, using monthly data from 2001 – 2007. The findings indicated that inflation causes IU and IU reduces inflation in the long run. This implies that the existence of FBH and C-M hypothesis does not hold.

Karanasos & Schurer (2008) measured IU as the conditional variance of Inflation in a power ARCH model and then examined the relationship between inflation and inflation uncertainty using monthly data for Germany, Netherlands and Sweden from 1962 to 2004. The findings support FBH in all the three countries. For Germany and Netherlands, higher IU increase inflation (C-M hypothesis), whereas, for Sweden, it reduces inflation (Holland Hypothesis).

Rizvi & Naqvi (2010) use bi-variate Granger causality to establish inflation-inflation uncertainty relationship in the Pakistani economy on quarterly data from 1976 to 2008. The findings showed the existence of bi-directional causality between inflation and inflation uncertainty. Findings on FBH is sensitive to the type of GARCH models adopted. For the standard GARCH model, the FBH do not hold. For the asymmetric GARCH models (EGARCH and gjrGARCH), FBH holds. In either of the GARCH type models, C-M hypothesis was consistently rejected.

Chowdhury (2011) examined inflation and inflation uncertainty in India. The finding showed a bi-directional relationship between inflation and inflation uncertainty implying the existence of FBH and C-M hypothesis.

Golob (1994) presented empirical evidence to explain the inconsistency in the inflation-inflation uncertainty in the US using the Livingston survey data. His observation implies that inflation and inflation uncertainty have a positive relationship and is downward trending. From the regression of estimated inflation on IU, it was observed that Inflation have a positive effect on IU. The IU estimates were derived by taking standard deviation of inflation forecast obtained from the survey data. This model also provides novel evidence in support of the downward trend in IU and concluded with evidence that this could explain why FBH does not hold in some studies.

Conrad & Karanasos (2005) use ARFIMA-FIGARCH to measure inflation uncertainty and adopt Toda and Yamamoto (1995) causality test to examine inflation-inflation uncertainty in the USA, Japan and UK for the period 1962M01 - 2000M12. Inflation leads to increase in inflation uncertainty in all the countries (FBH). IU increase inflation in Japan (C-M hypothesis). For UK, IU had a mixed effect on inflation. For US, C-M hypothesis does not exist.

Albulescu *et al.* (2015) examined inflation and inflation uncertainty in the US using annual data from 1775 - 2014. The study measured Inflation uncertainty using bounded model and stochastic volatility model and then adopt wavelet approach to examine causality between inflation and IU. The bounded model estimated IU showed support for C-M hypothesis, whereas Stochastic Volatility model estimated IU showed support for FBH. In all, FBH and C-M hypothesis only hold for the medium and long run.

Barnett *et al.* (2018) examined the relationship between inflation and inflation uncertainty in developed and emerging economies. They adopt a stochastic model to measure IU and the frequency evolutionary co-spectral approach and the continuous wavelet methodology to investigate FBH. Their findings showed the inflation-inflation uncertainty varies in time and frequency. FBH exists in the short and medium term period. During the crisis period, inflation decreases IU.

Ferreira & Palma (2016) examined the existence of time varying relationship between inflation uncertainty and inflation in Latin America using stochastic volatility in mean model. The monthly data span from January 1996 to February 2015. The study showed that IU and inflation had positive time varying relationship. An earlier study by Chan (2015) for US, UK and Germany showed similar time varying relation between inflation-inflation uncertainty.

Ftiti & Jawadi (2019) adopted GARCH models and stochastic volatility models to measure IU in US and Euro area. The study used monthly data which span from January 1997 to January 2017. Findings established that SV models performs best in out-of-sample forecast of IU. Stochastic volatility modelling of IU offers greater flexibility in measuring uncertainty. This finding supports Chan (2012) and Chan (2015) which highlighted that stochastic volatility models performs best in forecasting IU.

Griera & Perry (1998) is among the early work using time domain Granger causality to examine inflation and inflation uncertainty in G7 countries using monthly data from 1948 to 1993. The proxy for inflation uncertainty was derived using GARCH model to estimate conditional variance of inflation. The findings support the existence of FBH. The existence of C-M hypothesis is weak. For US, UK and Germany, an increase in IU leads to decrease in inflation. Conversely, increase in IU cause inflation to increase in Japan and France.

Bhar & Hamori (2004) estimated IU using Markov Switching heteroscedastic model and then examined the inflation-inflation uncertainty among G7 countries using quarterly data from 1961 - 1999. First, they observed that IU is best estimated for G7 countries using Markov Switching model when compared to GARCH type models. Their findings showed an increase in IU in the long-run increases inflation in Canada, Germany, and Japan, supporting C-M hypothesis. In addition, increase in IU in the short run increases inflation in Germany and USA while it decreases inflation in Canada.

Balcilar & Ozdemir (2013) examined inflation - inflation uncertainty for G7 countries using monthly data from 1959 - 2008. Inflation uncertainty was measured using FISTARMA-APARCH model. The MS-VAR model is further adopted to examine the relationship. This approach is suitable with the study assumption that inflation-inflation uncertainty has time varying causality. The findings showed a time varying relationship between inflation and inflation uncertainty in all countries across time. The study finding from the rolling Granger Causality supports strong time varying FBH for all the countries and weak evidence for time varying C-M Hypothesis for G7 countries.

The existing studies reviewed adopted several estimation methods in examining the inflation-inflation uncertainty. Common among the studies used two step method. In this method, an estimate for IU is derived by estimating proxy for inflation uncertainty. The Markov switching model is another option adopted.

Also, the second part of Inflation - IU relation involves testing for the directions of the relationship. The common method adopted in the literature reviewed is the time domain Granger causality test. This method assumes the relationship is linear and time invariant thereby ignoring the possibility of time varying causality. Albulescu *et al.* (2015) observed that the time-domain ignores the importance of the frequency-varying properties of inflation and its uncertainty. On this backdrop, some of the studies reviewed showed that inflation – IU relationship is nonlinear (Balcilar & Ozdemir (2013); Bouoiyour & Selmi (2014) and Albulescu *et al.* 2015). From the reviewed literature, the method adopted to examine nonlinear inflation – inflation uncertainty includes Markov Switching models, nonlinear (within Wavelet framework) causality test and rolling Granger Causality.

Existing studies that adopted time domain granger causality might not give a true inflation – inflation uncertainty relationship when these variables are nonlinear. This study resolves this problem by adopting transfer entropy that has the potential to reveal a more accurate relationship between inflation – inflation uncertainty. Existing study by Fernández-Valdovinos & Gerling (2011) is more than a decade old and cover some selected ECOWAS member states. This study extends the countries to cover more ECOWAS member states. In addition, from the country specific study, the member countries are underrepresented among the huge body of empirical literature examining the FBH and C-M hypothesis. This study attempts to fill this gap. Similarly, some of the reviewed studies are country specific. Recent among them is Bamanga *et al.* (2016) who adopt the time domain Granger causality which is not very efficient in capturing nonlinear relationships. The transfer entropy adopted in this study is quite receptive to linear and nonlinear properties.

3. Data and Methodology

3.1 Data

This study adopts monthly data on consumer price index (CPI) for ECOWAS members. The data were sourced from International Financial Statistics (IFS) of the International Monetary Fund. The log returns given as:

$$CPI = 100 * \log\left(\frac{CPI_t}{CPI_{t-1}}\right)$$

was used to measure inflation. Table 1 show the various sample periods for this study. Inflation uncertainty is then separately measured from the GARCH and stochastic volatility models. The CPI series for all countries were deseasonalized using the loess method developed by Cleveland *et al.* (1990).

Table 1: Sample periods

Country	Sample range	size
Benin	1991M12 to 2021M10	359
Burkina Faso	1960M01 to 2021M09	741
Cabo Verde	1992M01 to 2021M03	351
Côte d Ivoire	1960M01 to 2021M10	742
Ghana	1963M03 to 2021M10	704
Guinea	2004M01 to 2021M10	214
Guinea Bissau	1986M02 to 2020M07	414
Liberia	2001M01 to 2019M02	218
Niger	1968M01 to 2020M02	626
Nigeria	1960M01 to 2020M05	725
Senegal	1968M01 to 2021M04	640
Sierra Leone	2006M01 to 2021M07	187
The Gambia	1961M01 to 2021M10	730

3.2 Model Specification

3.2.1 GARCH and Stochastic Volatility Models

The conditional mean equation is needed in GARCH estimation procedure and it is given as:

$$\pi_t = c + \sum_{j=1}^{p} \rho_j \pi_{t-j} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

where π_t is log difference of CPI, c is constant, ρ_j are the coefficients of the autoregressive term of π_t at order p, θ_j is the vector of coefficient of the moving average of log difference of CPI at order q. The optimum order of p and q will be chosen based on AIC criteria. ε_t and ε_{t-j} are white noise.

The standard GARCH model (GARCH) of order p and q is given as:

$$\sigma_t^2 = \gamma_0 + \sum_{i}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

where p is the autoregressive term and q is the moving average term. The choice of p and q in this study is based on Bayesian information criterion for model selection. σ_t^2 is the conditional variance (volatility) used to measure inflation uncertainty. γ_0 is constant. α_i is the Autoregressive conditional heteroscedastic (ARCH) effect. It captures the adjustment level to shocks in ε_{t-i}^2. β_j is the GARCH effect showing the adjustment in σ_t^2 for a given shock in previous volatility. It shows the level of persistence in σ_{t-j}^2. The rate at which this persistence dies out is given by $\alpha_i + \beta_j$, which should be less than unity for covariance stationarity condition. For σ_t^2 to be all positive, γ_0, $\alpha_i > 0$ and $\beta_j \geq 0$.

GARCH (p, q) is a symmetric measure of conditional variance. Meanwhile, volatility response to shocks can be asymmetric. In this case, GARCH (p, q) estimates of σ_t^2 can be biased since it assumes positive and negative shocks on π_{t-j} have symmetric effect on σ_t^2. To resolve this, Nelson (1991) proposed the Exponential GARCH (EGARCH) model as a sound alternative to Bollerslev (1986) GARCH model presented in equation 2, in the presence of leverage effect in a series. The specification below is EGARCH (p, q):

$$\log\left(\sigma_t^2\right) = \gamma_0 + \sum_j^q \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_i^p \alpha_i \frac{\left|\varepsilon_{t-i}^2\right| + \delta_i \varepsilon_{t-i}^2}{\sigma_{t-i}} \tag{3}$$

where δ_i is leverage effect. It measures the asymmetric effect of shocks on log–conditional variance. For leverage effect to exist in volatility in this model, $\delta_i < 0$. This implied asymmetric effect since positive inflation shock leads to less uncertainty about inflation, vice versa. Stationarity is achieved when $\sum_j^q \beta_j < 1$.

A perfect alternative to EGARCH model is Glosten, *et al.* (1993) GARCH model (gjrGARCH). Indicator function helps in capturing the asymmetric response of shocks to π_{t-i} on conditional variance. GjrGARCH (p, q) model is given as:

$$\sigma_t^2 = \gamma_0 + \sum_j^q \beta_j \sigma_{t-j}^2 + \sum_i^p (\alpha_i + \delta_i I_{t-i}) \varepsilon_{t-i}^2 \tag{4}$$

where I_{t-i} is an indicator (dummy) variable which takes the value of 1 when $\varepsilon_{t-i} < 0$ and 0 for $\varepsilon_{t-i} \geq 0$. When the leverage effect $\delta_i > 0$, negative shock to ε_t causes the conditional variance adjust by $\alpha_i + \delta_i$. When $\delta_i = 0$, the leverage effect is not significant and gjrGARCH approximate the standard GARCH presented in equation 2. When $\delta_i < 0$, negative shocks have greater impact on the conditional variance than positive shock. The gjrGARCH specification is same as Threshold GARCH

(TGARCH) model. The gjrGARCH(p,q) model persistence $\widetilde{\mathrm{P}}$ is given as given as:

$$\widetilde{\mathrm{P}}=\sum_{j}^{q}\beta_j+\sum_{i}^{p}\alpha_i+\sum_{i}^{p}\delta_i k \tag{5}$$

where $k = E\left[I_{t-i}, Z_{t-i}^2\right]$. Z is the standardized residual below zero (see Ghalanos 2020 for more details on asymmetric model persistence).

GARCH estimate volatility of a time series by assuming the deterministic changes in the volatility. Stochastic Volatility (SV) model assumes the volatility process evolves in a stochastic and time varying manner (Hosszejni & Kastner, 2020). Stochastic volatility model is thus suitable in modelling time varying volatility and have gained increasing popularity in empirical studies since it was initially introduced by Taylor (1982). The SV model provides more flexible volatility than the asymmetric GARCH type model (Nakajima, 2012). On this basis, the study also considers the SV models as contained in Hosszejni and Kastner (2020)

$$\pi_t = \exp(h_t/2)\varepsilon_t$$

$$h_{t+1} = \mu + \varphi\,(h_t - \mu) + \sigma\eta_t \tag{6}$$

where h_t is the log variance process. β_0 is the constant, μ is level of the latent volatility process h_t. The model persistence is φ with stationary process $|\varphi| < 1$. σ is the volatility of log variance (volatility of volatility). ε_t and η_t have standard t distribution and normal distribution, respectively, and with zero mean and unit variance. The SV model without leverage effect ρ, imply correlation between ε_t and η_t is zero. Stochastic volatility model with leverage effect is estimated when $\rho \neq 0$,

$$\sum\rho = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$$

where $\sum\rho$ is the correlation matrix of ε_t and η_t. If $\rho < 0$, decrease in CPI is followed by increase in volatility.

Bayesian inference from (estimation of) SV model using Markov chain Monte Carlo (MCMC) algorithm requires assumption on the prior distribution. Drawing from existing literature, to ensure stationarity process, $\varphi\in(-1,\ 1)$. In addition,

Prior distributions:		
μ	$\sim$	N(mean = 0, sd = 100)
(φ+1)/2	$\sim$	N (a = 5, b = 1.5)
σ^2	$\sim$	Gamma(shape = 0.5, rate = 0.5)
N -2	$\sim$	Exponential(rate = 0.1)
ρ	$\sim$	β(a = 4, b = 4)

For detail discussion on the priors, see Hosszejni and Kastner (2020). The median of the posterior distribution of the estimated h_{t+1} is taken as the measure of inflation uncertainty.

3.2.2 Transfer Entropy

Let X and Y be stationary random variables with discrete values of

$$\mathrm{X} = x_t,\ x_{t-1},\ \ldots,x_{t-k+1}$$

$$\mathrm{Y} = y_t,\ y_{t-1},\ \ldots,y_{t-l+1} \tag{7}$$

where k and l are embedding dimensions (constant lags) for X and Y respectively. In this study, $k = l = 1$. x_t and y_t are the discrete states of X and Y, respectively at time t. The variable X and Y are assumed to have Markov properties of order k and l respectively:

$$\mathrm{X} = \mathrm{p}(x_{t+1}|x_t,\ \ldots,x_{t-k+1}) = p(x_{t+1}|x_t^{(k)})$$

$$\mathrm{Y} = \mathrm{p}(y_{t+1}|y_t,\ \ldots,y_{t-k+1}) = p(y_{t+1}|y_t^{(l)}) \tag{8}$$

where $p(x_{t+1}|x_t^{(k)})$ and $(y_{t+1}|y_t^{(l)})$ are the conditional probabilities. $p(x_{t+1}|x_t^{(k)})$ is probability (uncertainty) of finding X at state $t+1$ given the k dimensional vector, $x_t^{(k)}$. $p(y_{t+1}|y_t^{(l)})$ is the probability of finding Y at state $t+1$ given the l dimensional vector, $y_t^{(l)}$. $x_t^{(k)}$) and $y_t^{(l)}$ are discrete values for X and Y respectively.

The Shannon entropy for the discrete values is given as

$$H(X,Y) = \sum_{k=1} p\left(x_{t+1},x_t^{(k)},y_t^{(l)}\right) \log p(x_{t+1}|x_t^{(k)},y_t^{(l)}) \tag{9}$$

To derive the information flow from Y to X , first, let have a baseline Shannon entropy where $l = 0$ which implies probabilities of X being in state $t+1$ is independent of $y_t^{(l)}$. That implies X is independent of Y.

$$H(X) = \sum_{k=1} p\left(x_{t+1}, x_t^{(k)}\right) \log p(x_{t+1}|x_t^{(k)}) \tag{10}$$

Where $p(x_{t+1}|x_t^{(k)}, y_t^{(l)})$ is the probability of predicting discrete value of X, a step ahead (x_{t+1}) conditional on (given) $x_t^{(k)}$ and $y_t^{(l)}$.

Transfer entropy quantifies the deviation of the information contained in equation 9 from equation 10:

$$TE_{Y \to X} = H(X) - H(X,Y) \tag{11}$$

where $TE_{Y \to X}$ is the transfer entropy from Y to X. Transfer entropy is accredited to Schreiber (2000). Equation 11 measures the extent of deviation from the baseline model. Presence of deviation implies causality from Y to X.

For computational purpose, the conditional probabilities $p(x_{t+1}|x_t^{(k)}, y_t^{(l)})$ and $p(x_{t+1}|x_t^{(k)})$ in equation 9 and 10 respectively, are substituted with their probability density functions (PDFs) given as:

$$p\left(x_{t+1} \,\middle|\, x_t^{(k)}, y_t^{(l)}\right) = \frac{p(x_{t+1}, x_t^{(k)}, y_t^{(l)})}{p(x_t^{(k)}, y_t^{(l)})}$$

$$p\left(x_{t+1} \,\middle|\, x_t^{(k)}\right) = \frac{p(x_{t+1}, x_t^{(k)})}{p(x_t^{(k)})} \tag{12}$$

And the resulting model, after simplification is:

$$TE_{Y \to X} = \sum_{k=1} p\left(x_{t+1}, x_t^{(k)}, y_t^{(l)}\right) \log p \left(\frac{p(x_{t+1}, x_t^{(k)}, y_t^{(l)}) p(x_t^{(k)})}{p\left(x_t^{(k)}, y_t^{(l)}\right) p(x_{t+1}, x_t^{(k)})} \right) \tag{13}$$

Transfer entropy is a nonparametric test for causality. It is a sound alternative to Granger Causality and does not necessarily relied on model assumption such as linearity as observed in the time domain Granger causality measure. Similarly, TE has asymmetric properties and can capture the randomness of X and Y. For Bidirectional model, transfer entropy from X to Y is given as:

$$TE_{X\to Y} = \sum_{k=1} p\left(x_{t+1}, x_t^{(k)}, y_t^{(l)}\right) \log p \left(\frac{p(y_{t+1}, y_t^{(l)}, x_t^{(k)}) p(x_t^{(k)})}{p\left(y_t^{(l)}, x_t^{(k)}\right) p(y_{t+1}, y_t^{(l)})} \right) \tag{14}$$

Transfer entropy measure the extent at which two $(y_t^{(l)}, x_t^{(k)})$ discrete dimensional vectors influence prediction of one (of Y or X) variable at various states. When no information flow exist, $TE_{X\to Y}$ and $TE_{Y\to X}$ can both approached zero. If unidirectional information flow exist, either $TE_{X\to Y}$ or $TE_{Y\to X}$ will be greater than zero. For existence of bidirectional information flow, both $TE_{X\to Y}$ and $TE_{Y\to X}$ will be higher than zero. Dominant information flow exist from X (Y) to Y (X) when the values of $TE_{X\to Y}$ $(TE_{Y\to X})$ is greater than $TE_{Y\to X}$ $(TE_{X\to Y})$.

The values for $TE_{X\to Y}$ and $TE_{Y\to X}$ are biased in small sample sizes (Marschinski and Kantz, 2002 as cited in Behrendt *et al.* 2019). To correct for biasedness, Marschinski and Kantz (2002) proposed effective transfer entropy which is derived as:

$$\begin{aligned} ETE_{Y\to X} &= TE_{Y\to X} - TE_{Yshuffled\to X} \\ ETE_{X\to Y} &= TE_{X\to Y} - TE_{Xshuffled\to Y} \end{aligned} \tag{15}$$

where $TE_{Yshuffled\to X}$ $(TE_{Xshuffled\to Y})$ is the transfer entropy, derived by random shuffling of Y (X) in establishing $Y's$ $(X's)$ influence on X (Y).

3.3 Model Estimation Procedure

Countries with incomplete data or at least, a break in CPI are excluded. Then check for non-stationarity will be conducted. To ascertain if a series can be modelled for volatility, this study test for heteroscedasticity using up to 5 lags for all the available member states' CPI. Variables having homoscedastic returns are excluded. The inflation uncertainty is then modelled as conditional variance derived from the GARCH models (using R package rugarch, version 1.4-4 of Ghalanos, 2020) and stochastic volatility modelling method (using R package stochvol, version 3.0.3 of Hosszejni & Kastner 2020). Effective Transfer entropy is then measured (using R package RTransferEntropy version 0.2.13 of Behrendt *et al.* 2020).

4. Results and Discussions

Table 2: Descriptive Statistics

Country	Mean	SD	Min	Max	kurtosis
Benin	0.31	1.55	-3.88	16.45	32.33
Burkina Faso	0.33	2.84	-13.71	15.82	6.56
Cabo Verde	0.21	0.93	-5.18	6.78	11.68
Cote d Ivoire	0.42	1.81	-10.39	14.7	14.19
Ghana	1.83	3.11	-20.63	21.51	11.94
Guinea	1.14	6.12	-57.78	61.14	81.22
Guinea Bissau	1.34	4.02	-13	24.62	7.59
Liberia	0.88	1.61	-3.77	9.42	3.43
Niger	0.34	2.19	-17.15	14.66	12.16
Nigeria	1.16	1.93	-9.7	11.01	4.16
Senegal	0.37	1.79	-7.08	12.44	7.89
Sierra Leone	0.76	0.66	-1.31	2.86	1.45
The Gambia	0.62	2.11	-7.63	11.75	5.45

On Table 2, Ghana seems to have the highest average CPI value among the ECOWAS member states followed by Guinea Bissau and Nigeria. Guinea has the fourth largest average CPI, but having the highest extreme fluctuation (SD) among the ECOWAS countries. This could mean Guinea placed less effort on price stabilization compared to other member states. Ghana whose CPI is the highest has the third extreme fluctuation. The member state with the least average CPI is Cabo Verde with a mean value of 0.21. The country volatility is not the least but Sierra Leone with minimum extreme fluctuation of 0.66 and the sixth highest average CPI of 0.76.

Westfall (2014) pointed out that kurtosis is about extremity of a tail distribution. This test reveals the nature of outliers in a time series. At first, the kurtosis for all the countries are positive, suggesting that the distribution of CPI returns follows t distribution. This implies the CPI returns for all countries have heavier tail distribution than normal distribution. Kurtosis above 3 implies leptokurtic. This is true for all the countries except Sierra Leone. This implies no extremity in the distribution of Sierra

Leone.

4.2 ARCH Test

Table 3: ARCH test

	lag 1	lag 2	lag 3	lag 4	lag 5
Benin	8.42***	9.58***	9.8**	9.77**	9.74
Burkina Faso	55.5***	80.54***	83.29***	104.05***	104.36***
Cabo Verde	33.1***	33.22***	33.91***	34.14***	34.03***
Cote d'Ivoire	21.31***	21.81***	26.4***	26.56***	29.22***
Ghana	208.48***	211.33***	224.94***	225.17***	224.91***
Guinea	51.37***	68.7***	76.17***	80.81***	83.19***
Guinea Bissau	9.39***	12.85***	15.95***	16.85***	34.04***
Liberia	0.12	0.87	0.73	1	1.12
Niger	50.09***	53.91***	86.42***	87.54***	87.9***
Nigeria	109.46***	120.42***	129.29***	129.42***	129.37***
Senegal	66.45***	74.02***	75.4***	75.29***	81.73***
Sierra Leone	19.42***	19.31***	20.45***	22.46***	22.98***
The Gambia	48.03***	51.87***	61.67***	69.2***	84.5***

Note 1: (***) 0.01, (**) 0.05 and (*) 0.1

Test for ARCH effect is the first step towards assessing the conditional variance in a time series. A common test in the literature is the Lagrange multiplier of Engle (1982). The null hypothesis for this test is homoscedasticity (no ARCH effect) (Tsay, 2005). Rejecting the null implies the presence of ARCH effect in the time series and the conditional variance can then be measured. The null hypothesis was tested using several lags (1 to 5). From Table 3, the null hypothesis is not rejected for Liberia's CPI at all lag values and thus excluded since the CPI contains no ARCH effect.

4.3 Unit Root Tests

Table 4: ADF and Phillips-Perron tests

	PP	ADF
	const [const & trend]	const [const & trend]
Benin	-16.61*** [-16.86***]	-12.29*** [-12.59***]
Burkina Faso	-34.35*** [-34.49***]	-21.9*** [-21.96***]
Cabo Verde	-19.51*** [-19.88***]	-13.75*** [-14.13***]
Cote d Ivoire	-29.84*** [-30.07***]	-20.73*** [-20.93***]
Ghana	-17.84*** [-17.95***]	-12.17*** [-12.3***]
Guinea	-30.67*** [-32.29***]	-16.68*** [-16.97***]
Guinea Bissau	-18.27*** [-20.29***]	-12.43*** [-14.82***]
Niger	-25.09*** [-25.31***]	-17.41*** [-17.64***]
Nigeria	-21.12*** [-21.18***]	-12.92*** [-12.97***]
Senegal	-26.55*** [-26.99***]	-16.93*** [-17.35***]
Sierra Leone	-9.8*** [-10.39***]	-7.34*** [-8.05***]
The Gambia	-30.14*** [-30.12***]	-19.81*** [-19.8***]

Note 2: (***) 0.01, (**) 0.05 and (*) 0.1

Though, log returns adopted in this study often gives a stationary process for a series. Verification of this is essential for time series analysis. To establish this fact, the common test in the literature for stationarity of a series is presented in Table 4 and 5. Table 5 presents the Zivot and Andrews (1992) structural break point test for unit root test. The null hypothesis is the absence of exogenous break point. The results show that CPI returns are stationary with an endogenously determined break date across the sample range for each member state. The classical ADF and Phillips-Perron tests presented in Table 4 consistently show that the CPI in log difference are stationary for all member states.

To get the best GARCH models for each country, this study adopts Perlin *et al.* (2020) R codes. A series of different specifications for GARCH models using sGARCH, eGARCH, gjrGARCH, apGARCH and FIGARCH with variants AR and MA values (0,1) and two different types of distributions which include normal and t distributions. The models with the least BIC are presented in Table 6. The GARCH models specification was done using the BIC criterion presented above. The result for each member states are attached as appendix. Our interest is the estimates of the conditional volatilities. Hence, only a peripheral discussion was placed on model interpretation in the appendix.

Table 5: Zivot Andrews test

	const	break date	const and trend	break date
Benin	-9.29***	Nov 1994	-11.18***	Nov 1994
Burkina Faso	-13.16***	Dec 1972	-13.22***	Dec 1972
Cabo Verde	-9.19***	Jan 1999	-9.3***	Apr 2005
Cote d Ivoire	-12.88***	Jun 1972	-13.02***	Sep 1980
Ghana	-10.88***	Sep 1973	-10.93***	May 1983
Guinea	-10.31***	Nov 2006	-10.26***	Nov 2006
Guinea Bissau	-9.74***	May 1997	-9.92***	May 1997
Niger	-11.41***	Aug 1981	-11.67***	Aug 1981
Nigeria	-8.82***	Jun 1996	-9.15***	Jun 1996
Senegal	-11.15***	Feb 1986	-11.57***	May 1975
Sierra Leone	-6.31***	Feb 2016	-6.56***	Mar 2016
The Gambia	-12.14***	Apr 1992	-12.98***	Mar 1987

Note 3: (***) 0.01, (**) 0.05 and (*) 0.1

Table 6: Best GARCH models estimation

	Mean equation	Variance equation	Distribution
Benin	ARMA(0,0)	sGARCH(1,1)	std
Burkina Faso	ARMA(0,1)	eGARCH(1,1)	std
Cabo Verde	ARMA(0,0)	sGARCH(1,1)	std
Cote d Ivoire	ARMA(1,1)	fiGARCH(1,1)	std
Ghana	ARMA(1,1)	eGARCH(2,1)	std
Guinea	ARMA(1,1)	apARCH(1,1)	std
Guinea Bissau	ARMA(1,1)	gjrGARCH(1,1)	std
Niger	ARMA(0,0)	eGARCH(2,1)	std
Nigeria	ARMA(1,1)	eGARCH(1,1)	std
Senegal	ARMA(0,0)	sGARCH(1,1)	std
Sierra Leone	ARMA(1,1)	sGARCH(1,1)	std
The Gambia	ARMA(1,0)	sGARCH(1,1)	std

Note 4 :ARMA is Autoregressive(AR) Moving Average(MA); eGARCH is exponential GARCH; sGARCH is standard GARCH; gjrGARCH is Glosten, Jagannathan, & Runkle GARCH; fiGARCH is Frictionally Integrated GARCH; apGARCH is asymmetric power ARCH model; std is the student t distribution.

4.4 Inflation-inflation Uncertainty Nexus in WAMZ and WAEMU

The study of Rizvi and Naqvi (2010) showed how establishing inflation-inflation uncertainty can be sensitive to the method adopted in measuring inflation uncertainty (IU). From the study, FBH does not exist when IU is measured using standard

GARCH model except when IU is measured using gjrGARCH. On this basis, this study also examined how causality exists when inflation uncertainty is measured under different model assumptions. Figure 2 and 3 show the GARCH and stochastic volatility models measured inflation uncertainty.

The information flows between inflation and inflation uncertainty among members of WAEMU are presented in Figure 2 and 3. The extended lines are the 95% confidence intervals. Statistical insignificance is established when zero lies within the confidence interval. Panel A of Figure 2 indicates that the information flow from inflation to GARCH measure of inflation uncertainty for WAEMU. The result show significant information flow from inflation to inflation uncertainty thus, providing a broader support for the likelihood of FBH and Pourgerami and Maskus (1987) hypothesis. Depending on the welfare cost of IU, the policy action of the monetary authority in response to inflation should be gauged. In the case where increasing inflation uncertainty negate societal benefit, the monetary authorities have to disinflate given the information flow from inflation to IU. Panel B of Figure 2 show the reverse flow from inflation uncertainty to inflation. In this case, statistically significant information flow exists in Burkina Faso only thus providing no support for the C-M and Holland (1995) hypotheses for the rest members of WAEMU. These hypotheses both agree on information flow from IU to inflation but vary on the directions. For the C-M, inflation uncertainty increases inflation, whereas, Holland (1995) posits it decreases inflation.

In panel C of Figure 2, time varying volatility was adopted in establishing the information flow in all the WAEMU states. Surprisingly, there is no statistical support for causality from inflation to IU for all the member states except Burkina Faso. For the reverse flow presented in panel D, it shows that causality exist from IU to inflation in all the member states, thus providing support to C-M and Holland (1995) hypotheses. Again, this shows that in all the member states except Burkina Faso, the hypothesis on inflation – IU relationship is sensitive to how IU is measured. This finding is in line with Albulescu *et al.* (2015) and of Rizvi and Naqvi (2010).

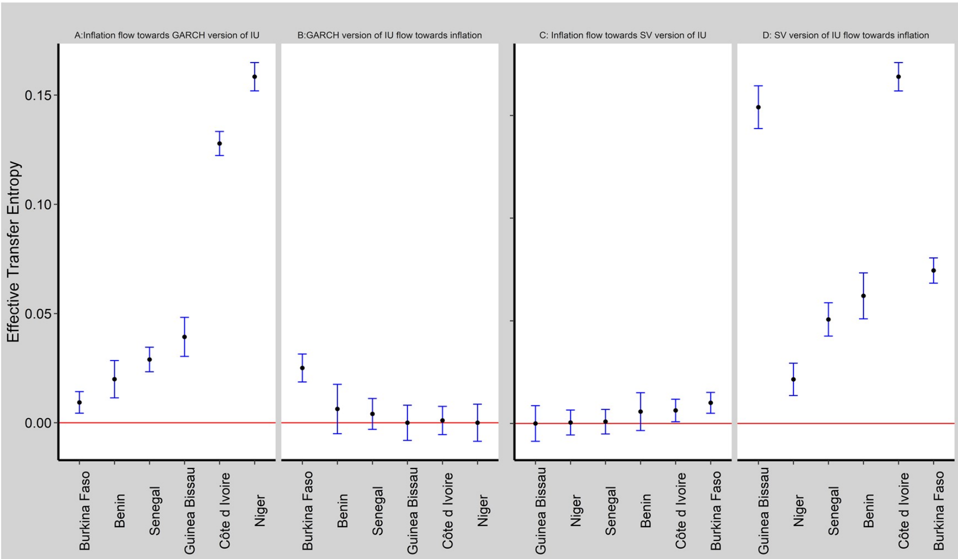

Figure 2: WAEMU information flow between inflation and IU

The results for the information flow from inflation to GARCH variants of IU is presented in Figure 3 for WAMZ. Panel A of Figure 3 shows the information flow from inflation to GARCH measured IU. There is statistically significant information flow from inflation to the IU for all the countries. Same observation is made for WAEMU in Figure 2 panel A. The reverse flow presented in panel B of Figure 3 indicates the absence of information flow from IU to inflation in all the countries except The Gambia thus providing broader support for the absence of C-M and Holland (1995) hypothesis in virtually all the member states. This finding is in line with Bamanga *et al.* (2016) for the case of Nigeria. For the asymmetric bidirectional causality that exist for The Gambia, Mendy and Widodo (2018) only support unidirectional flow from inflation to IU in The Gambia.

Figure 3 panel C and D present the SV variant of IU. Most of the findings contrast GARCH measure of IU. There is absence of information flow from inflation to IU for all the member states with exception to Cabo Verde which is neither WAMZ nor WAEMU member. Asymmetric bidirectional flow exists for the inflation – IU relationship in Cabo Verde by virtue of the results presented in panel D in Figure 3. For Nigeria, there is very weak support for asymmetric flow. Whereas, there is a unidirectional flow from IU to inflation for the rest members.

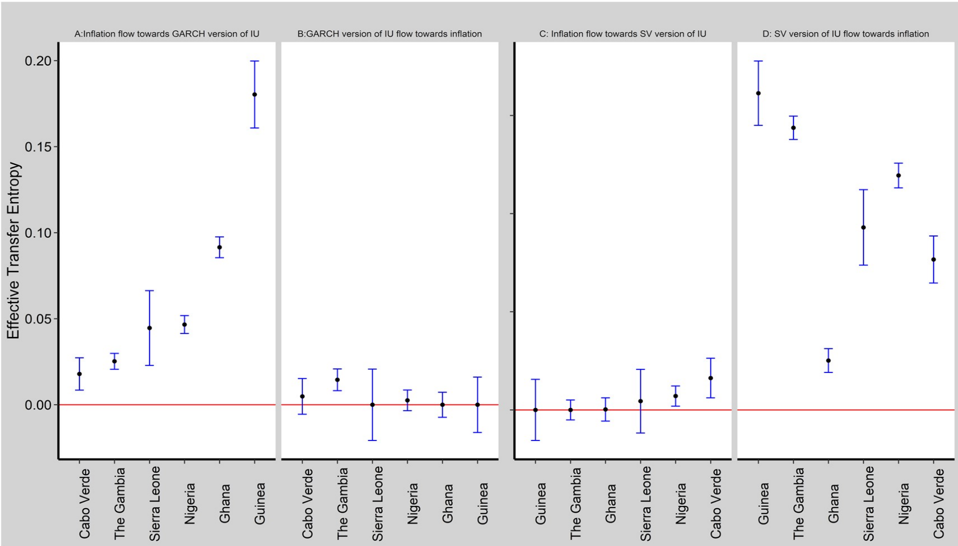

Figure 3:WAMZ and Cabo Verde information flow between inflation and IU

4.6 Intra Country Transfer Entropy for Inflation Trend

This study assesses the assertion of Fernández-Valdovinos and Gerling (2011) that inflation among the member states does transmit across borders. This study reviews the nature of intra WAMZ - WAEMU inflation relation in light of information theory. Unlike transfer entropy, correlation method adopted by Fernández-Valdovinos and Gerling (2011) is a symmetric method for estimating correlation between two variables. From the general perspective, if two variables are correlated it does not mean one variable causes the other, or vice versa. In addition, being a linear method, it does not provide information on cause and effect among the two variables (Jizba *et al.* 2012). Unlike Fernández-Valdovinos and Gerling (2011) whose study adopted Hodrick-Prescott (HP) filter to estimate the CPI trend for WAEMU, this study adopts Hamilton (2017) filter to estimate the CPI trend for each member. The latter filter is said to perform better, compared to HP filter.

Table 7 presents the transfer entropy for WAMZ intra CPI trend obtained using Hamilton filter on log CPI of WAMZ states. First, from the Transfer Entropy (TE) matrix, there is bidirectional asymmetric information flow among member states, particularly between Ghana and Guinea, Ghana and Sierra Leone, Guinea and Liberia, Guinea and Nigeria. These WAMZ members' CPI are interdependent and possess information that could help predict CPI trend in these countries. On the magnitude, Guinea information transfer to Nigeria dominates the reverse flow from Nigeria to Guinea. Similarly, Guinea shows same dominant information flow to Ghana compared to the reverse flow. There is no information flow from other WAMZ members to The Gambia. In conclusion, inflation trend of WAMZ are interconnected and that shocks in one country may transmit to others except for The Gambia.

Table 7: Transfer entropy for intra inflation trend of WAMZ

	Ghana	Guinea	Liberia	Nigeria	Sierra Leone	The Gambia	MCB (%)
Ghana	NA	0.04	0	0	0.01	0	6
Guinea	0.115	NA	0.024	0.024	0	0	20
Liberia	0.145	0.003	NA	0	0.014	0	20
Nigeria	0.146	0.001	0	NA	0.016	0	20
Sierra Leone	0.106	0.027	0	0	NA	0	16
The Gambia	0.107	0.032	0.005	0.007	0	NA	18

Sample range: 2008M12 to 2019M02

The marginal contribution (MCB) of each WAMZ member to total transfer entropy on Table 7 shows that Guinea, Liberia and Nigeria CPI shocks have the greatest effect on other WAMZ member states within the study period. The marginal impact on total TE is 20 percent each. This could be due to improved economic integration unfolding among these nations via improved regional trades. The less influential countries are Ghana and Sierra Leone with a contribution MCB of 6 and 16 per cent respectively. The goal of single digit inflation target of WAMZ is strongly at the mercy of majority of WAMZ member states. By implication, unification of monetary policy on price stability among the WAMZ could be effective.

Table 8 presents the transfer entropy matrix for intra CPI trend obtained using Hamilton filter on log CPI of WAEMU members. The matrix shows that the WAEMU member state's CPI trends are interdependence. Cote d'Ivoire has the highest information transfer to Guinea Bissau whereas the reverse flow does not exist. This indicates unidirectional flow for Cote d'Ivoire and Guinea Bissau. Other WAEMU members with intra unidirectional flow are Cote d'Ivoire to Niger, Cote d'Ivoire to Senegal, Burkina Faso to Senegal, Niger to Senegal. With exception to Cote d'Ivoire and Burkina Faso (no intra information flow), all other member groupings possess bidirectional causality. This implies that within the study period, all WAEMU members' CPI trends are interconnected making harmonization of policies on price stability look very appealing for WAEMU member states.

Table 8: Transfer entropy for intra inflation trend of WAEMU

	Benin	Burkina Faso	Guinea Bissau	Cote d'Ivoire	Niger	Senegal	MCB (%)
Benin	NA	0.019	0.073	0.026	0.034	0.013	20
Burkina Faso	0.033	NA	0.086	0	0.004	0.015	17
Guinea Bissau	0.014	0.002	NA	0	0.011	0.044	9
Cote d'Ivoire	0.041	0	0.089	NA	0.02	0.003	18
Niger	0.033	0.019	0.089	0	NA	0.043	22
Senegal	0.042	0	0.076	0	0	NA	14

Sample range: 1994M11 to 2020M02

The marginal contribution of each WAEMU member to total transfer entropy as shown in Table 8, shows that CPI in Benin, Niger and Cote d'Ivoire are the most influential transmitting 20 percent, 22 per cent and 18 per cent respectively, of the total information flow of WAEMU states. Less influential country among the reviewed members is Guinea Bissau. Price stability as contained in article 8 stipulates inflation range of 2 ± 1 percentage point. WAEMU convergence criteria entails harmonization of macroeconomic variables and 3 per cent single digit inflation. Giving the bidirectional flow, harmonization of policies on price stability is essential in meeting inflation target.

5. Conclusions and Recommendations

This study adopted Transfer entropy (TE) to examine information flow among ECOWAS member states. This method is dynamic when compared to Granger causality and serves as a suitable option for examining causality given its superior power over Granger Causality in capturing nonlinearity among economic variables in a uni-(bi) directional model.

The findings show the information flow between inflation and inflation uncertainty is influenced by how inflation uncertainty is estimated. This study provides a broader evidence in support of similar observation made by Albulescu *et. al.* (2015). Information flow does exist from inflation to IU when GARCH variants are adopted thus supporting the FBH and PM & UZ hypothesis. Conversely, when stochastic model is adopted to measure IU, we find no evidence for either FBH or PM & UZ hypothesis.

Similarly, when IU is estimated using GARCH variant models, there is no information flow from IU to inflation in most countries thus debunking the Holland and CM hypotheses. Nevertheless, when IU is obtained using SV model, we find information flow from IU to inflation, indicating a broader support for Holland and CM hypotheses.

This study finding is in line with existing literatures. For instance, for country specific study, Bamanga *et. al.* (2016) support FBH against CM for Nigeria when they measured IU using EGARCH. This study provides a much broader perspective for the mixed results on the inflation - IU relationship documented in the empirical literature. Irrespective of the block each member of ECOWAS belongs, with exception to Burkina Faso, The Gambia and Cabo Verde, the existence of FBH, PM & UZ hypothesis, C-M and Holland (1995) hypotheses are sensitive to how IU is measured. Comparing the information flow from IU to inflation under SV measure of IU, it may appear, inflation is more driven by SV measure of IU in WAMZ than WAEMU. However, for information flow from inflation to GARCH measure of IU, it is most likely that there is no significant difference in the magnitude of the flow across each member state of ECOWAS.

TE enables us to assess the asymmetric flow among member states of WAMZ CPI trends. It was observed, that CPI in WAMZ members states are interdependent. The findings show CPI trend of WAMZ are interconnected (coupled) and that shocks in one country may transmit to others except for The Gambia. The marginal contribution of each WAMZ member to total transfer entropy show that Guinea, Liberia and Nigeria CPI shocks have the greatest effect on other WAMZ member states within the study period. The less influential countries are Ghana and Sierra Leone. Same as WAMZ CPI trends, it was also observed that WAEMU member states CPI trends are coupled. With exception to Cote d'Ivoire and Burkina Faso (no intra information flow), all other member groupings possess asymmetric bidirectional causality. The marginal contribution of each WAEMU member to total transfer entropy indicated that CPI in Benin, Niger and Cote d'Ivoire are the most influential transmitting

20 percent, 22 percent and 18 percent respectively, of the total information flow of WAEMU states. Less influential country among the reviewed members is Guinea Bissau.

These findings have policy implications. First, harmonization of monetary policy on price stability of the economic blocs within ECOWAS might be effective given their interdependence. This study encourages further discussion on in-sample and out-of-sample performance of SV models in forecasting inflation for West African countries. Also, this study encouraged regional comparison of inflationary trend while factoring individual country's structural differences among the ECOWAS member states. Lastly, this study also observe that the precise estimate of TE can vary depending on the choice of the quantile. Behrendt, *et al.* (2019) hinted at this precise estimate. In this case, robustness across each choice of quantiles is essential irrespective of whatever quantile values are adopted.

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Appendix

Volatility estimates

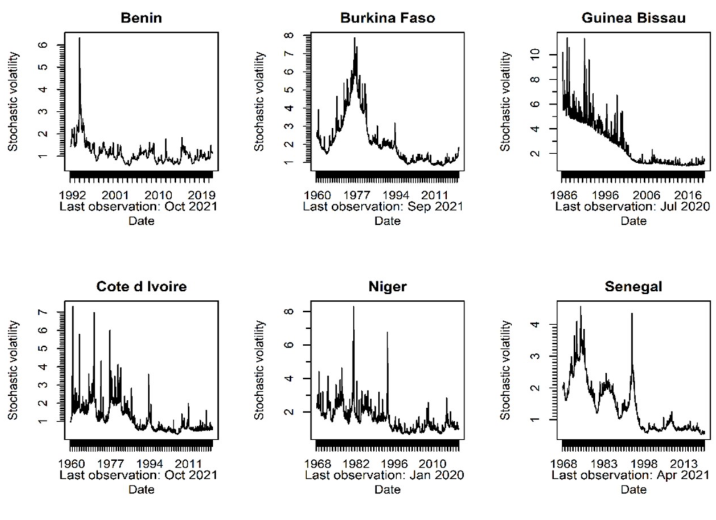

Figure 4:Stochastic volatility estimates for WAEMU

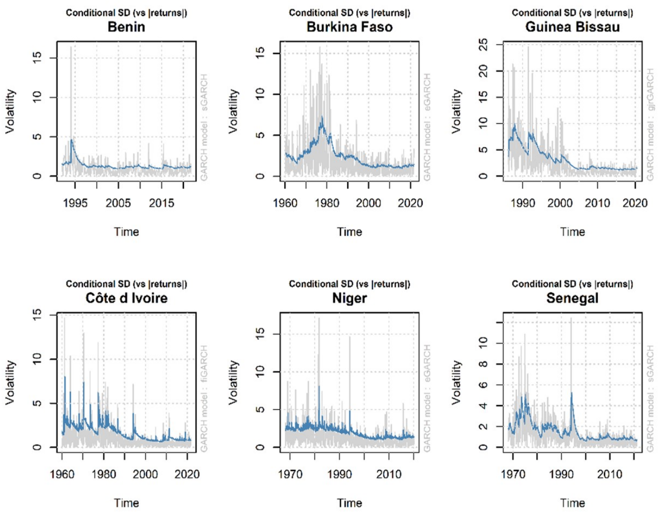

Figure 5:GARCH volatility estimates for WAEMU

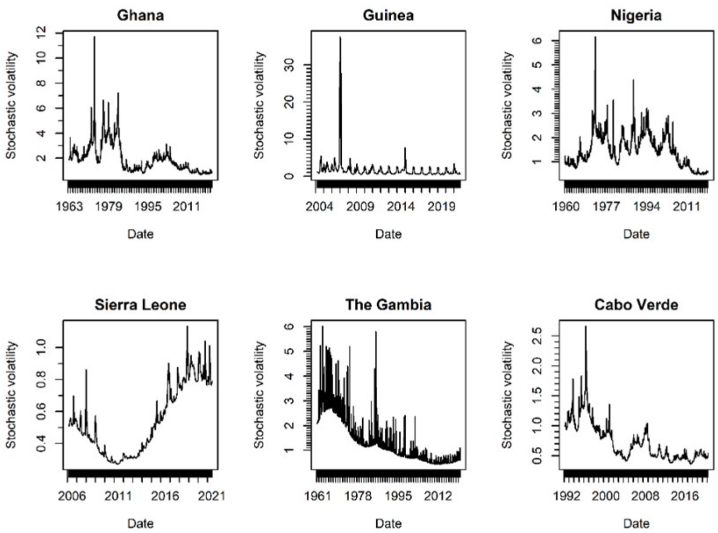

Figure 6:Stochastic volatility estimates for WAMZ and Cabo Verde

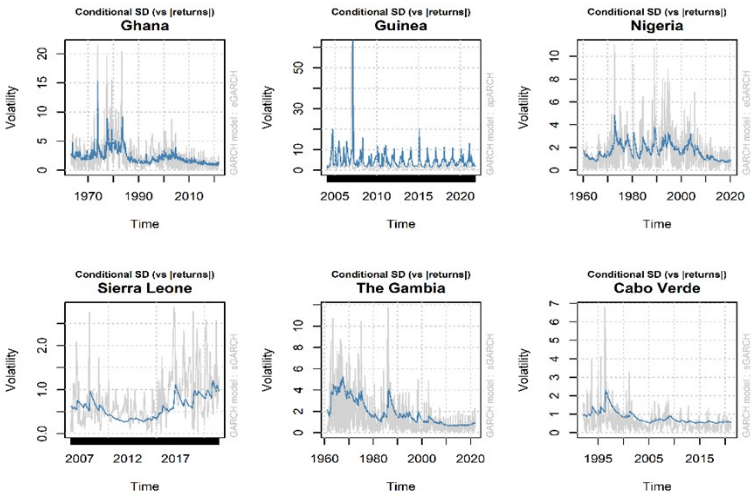

Figure 7:GARCH volatility estimates for WAMZ and Cabo Verde

Table 9: GARCH models for WAMZ

	Ghana	Guinea	Nigeria	Sierra Leone	The Gambia	Cabo Verde
mu	1.403***	0.236***	0.892***	0.486**	0.486***	0.111**
	(0.2)	(0.01)	(0.09)	(0.16)	(0.04)	(0.04)
ar1	0.729***	0.964***	0.758***	0.987***	0.150***	
	(0.07)	(0.01)	(0.04)	(0.02)	(0.04)	
ma1	-0.312***	-0.895***	-0.418***	-0.910***		
	(0.09)	(0.01)	(0.06)	(0.04)		
omega	0.024**	0.805	0.017*	0.005	0.014	0.015
	(0.01)	(0.64)	(0.01)	(0.01)	(0.01)	(0.01)
alpha1	0.056	0.584	0.064*	0.135**	0.072***	0.061
	(0.06)	(0.72)	(0.03)	(0.05)	(0.02)	(0.04)
alpha2	0.011					
	(0.06)					
beta1	0.978***	0.193	0.976***	0.864***	0.927***	0.909***
	(0.00)	(0.14)	(0.00)	(0.05)	(0.02)	(0.05)
gamma1	0.525***	-0.940***	0.218***			
	(0.09)	(0.06)	(0.02)			
gamma2	-0.343***					
	(0.09)					
shape	4.369***	2.102***	4.218***	5.401**	3.408***	5.125***
	(0.79)	(0.02)	(0.69)	(2.08)	(0.41)	(1.26)
delta		0.335				
		(0.57)				
Variance Model	eGARCH	apARCH	eGARCH	sGARCH	sGARCH	sGARCH
Distribution	std	std	std	std	std	std
Model Persistence	0.978	0.47	0.976	0.999	0.999	0.971
Convergence	0	0	0	0	0	0
N	703	213	724	186	729	350
Log likelihood	-1439.91	-391.445	-1295.96	-147.076	-1288.799	-392.906
AIC	4.125	3.76	3.602	1.657	3.552	2.274
BIC	4.19	3.902	3.653	1.778	3.59	2.329

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table 10: GARCH models for WAEMU

	Benin	Burkina Faso	Guinea Bissau	Côte d'Ivoire	Niger	Senegal
mu	0.174**	0.148**	0.093	0.203**	0.204***	0.159***
	(0.06)	(0.05)	(0.27)	(0.07)	(0.04)	(0.04)
omega	0.091	0.004	0.066*	0.009*	0.003	0.03
	(0.05)	(0.00)	(0.03)	(0.00)	(0.00)	(0.02)
alpha1	0.071	-0.061**	0.092**	0.256	0.023	0.138***
	(0.04)	(0.02)	(0.04)	(0.14)	(0.07)	(0.03)
beta1	0.872***	0.999***	0.929***	0.963***	0.995***	0.855***
	(0.06)	(0.00)	(0.02)	(0.01)	(0.00)	(0.03)
shape	4.615***	5.750***	4.171***	2.926***	3.772***	6.277***
	(1.05)	(1.26)	(0.85)	(0.19)	(0.58)	(1.37)
ma1		-0.177***	-0.961***	-0.967***		
		(0.04)	(0.01)	(0.01)		
gamma1		0.123***	-0.086*		0.399***	
		(0.02)	(0.04)		(0.10)	
ar1			0.988***	0.985***		
			(0.00)	(0.01)		
delta				1.000***		
				(0.11)		
alpha2					-0.014	
					(0.07)	
gamma2					-0.338***	
					(0.09)	
Variance Model	sGARCH	eGARCH	gjrGARCH	fiGARCH	eGARCH	sGARCH
Distribution	std	std	std	std	std	std
Model Persistence	0.943	0.999	0.978	0.537	0.995	0.992
Convergence	0	0	0	0	0	0
N	358	740	413	741	625	639
Log likelihood	-575.92	-1559.18	-950.822	-1166.659	-1220.88	-1078.4
AIC	3.245	4.233	4.643	3.17	3.932	3.391
BIC	3.3	4.276	4.721	3.22	3.989	3.426

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Model persistence is less than one in all the member states. The model for the members converges. Here, zero implies convergence achieved. N is the total sample used in the estimation. Mu is constant of the mean equation. Omega is constant of the GARCH model equations. alpha1 is ARCH effect coefficient of lag 1. First, for all the member states except Burkina Faso, the assumption of positive ARCH effect is met. Statistical significance is only established in 6 member states. This positivity of ARCH effect for every standard GARCH model. Alpha2 is ARCH effect coefficient of lag 2. Beta1 is GARCH effect coefficient of lag 1. The positivity of GARCH effect is attained and statistically significant for all member states. ma1 is moving average of order 1. ar1is autoregressive of order 1. Gamma1 is the coefficient of the leverage effect at lag 1 while gamma2 is at same coefficient of leverage at lag 2.