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Analyzing Inflation Dynamics in Ghana: Evidence as of Quantile Autoregressive Model

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Abstract

Inflation persistence (or inertia) has been a problem in many developing countries and due to the relationship between inflation and economic growth, much research has been conducted on the literature to study closely these macroeconomic variables in developing countries (Brick, 2010; Gokal and Hanif, 2004). This paper however made use of a superior method known as quantile autoregressive model proposed by Koenker and Xiao (2006) to estimate the persistence of inflation, the dynamic behavior and examine how diverse shocks may perhaps affect the rate of inflation within different quantiles. The data employed in this study is the monthly year-on-year Ghana inflation rate from January 2000 to July 2019. The result shows that Ghana inflation rates exhibits low persistence at both lower and higher quantiles and a mean reversion behavior across quantiles. Also, we observe that Ghana inflation rate is globally stationary as well as portraying non-stationary behavior in about 10% of the sampled observations. Evidently, the results again reveal that Ghana inflation rate has irregular characteristics at different quantiles in its conditional distribution. Also, there is a bidirectional relationship between Ghana overall inflation rate and its components (food and non-food inflation).

Keywords: Inflation, Quantile autoregressive, Ghana, Persistence, Food and Non-food indices.

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Introduction

Inflation persistence (or inertia) has been a problem in many developing countries (Gerlach and Tillmann, 2012; Mallick and Sousa, 2012; Ocran, 2007; Phiri, 2016; Vega and Winkelried, 2005) and due to the relationship between inflation and economic growth, much research has been conducted on the literature to study these two closely macroeconomic variables in developing countries (Brick, 2010; Gokal and Hanif, 2004). Inflation persistence is related to how quickly a stationary inflation process reverts to its initial level, long-run equilibrium or inflation target after a shock. Inflation persistence is still a relevant concern in economics for several reasons.

According to Phiri (2016b), commitment to price stability forms the epitome of present day monetary policy and Central Banks worldwide have agreed to this commitment, either by statutory mandates or by designated exercises of discretion. As conveniently noted by Phiri (2012), an inflation process exhibiting low levels of persistence reflects a financial environment in which policymakers can control the inflation process. Conversely, high levels of inflation persistence signal the inability of Central Banks to control inflation such that any deviations of inflation from its steady-state will ensure that inflation does not easily adjust back to its long-run equilibrium (Mavikela et al., 2018).

According to Piazza et al., (2018), the latest World Economic Outlook (WEO) report published by the International Monetary Fund (IMF, 2017) projected double-digit inflation (or more) for 23 countries in 2017 (e.g., Angola 30.9%; Egypt 23.5%; Ukraine 12.8%; Turkey 10.9%). Although the report projects consumer price inflation in 2017 (annual percent change) of 1.7% for the advanced economies and 4.2% for the emerging market and developing economies, these figures are very heterogeneous among countries. For instance, inflation forecasts for Brazil and Chile in 2017 are 3.7% and 2.3%, respectively, whereas for Argentina the figure is 26.9% and for Venezuela 652.7%. On the other hand, inflation persistence directly affects the output costs of bringing inflation back to the target, often described in the literature as the sacrifice ratio. In other words, persistent inflation increases the costs of monetary policy to keep inflation under control, since rapid reductions of inflation are produced at the cost of substantial increase in unemployment and/or decrease of output (Mishkin, 2007). For instance, emerging economies which exhibit high inflation persistence may need to adjust macroeconomic policies in a substantial way to price shocks given that these might influence overall inflation (and inflation expectations) for a sustained period.

Evidence from previous studies shows that inflation targeting has generally been successful in reducing the inflation persistence, particularly in developing economies (Lin and Ye, 2009; Mendonça and Souza, 2012; Gonçalves and Salles, 2008; Samarina et al., 2014; Schmidt-hebbel and Mishkin, 2007; Stock and Watson, 2007; see Walsh, 2009, for a useful survey). We define inflation targeting as a conduct of monetary policy where a central bank has price stability as its primary objective, publicly announces a medium-term numerical target inflation and commits to it, and uses the inflation forecast as an intermediate target. However, one country where inflation targeting seems to have been singularly unsuccessful is Ghana, the first low-income country in Africa to adopt inflation target. Like most African countries, Ghana has experienced high inflationary periods in the past especially in the 1980s and early 1990s, reaching a maximum of 174.1% in June of 1983 from nearly 17.7% inflation a year earlier. Ghana continued to witness high inflation until recently when inflation recorded a lower-double digit of 10.2% in April 1999 and single digit for a very long time in June 2010 (9.52%) due to policy shift and adoption of inflation-Targeting regime or framework which represents a sharp deviation from earlier monetary-Targeting regime (Osei, 2015).

The 1960s and 1970s were considered periods of high (and persistent) inflation in such countries, while more recent years have seen low levels of inflation and persistence (Piazza et al., 2018). For instance, there has been a reduction of persistence in the U.S., especially after the 1990s, due to the great moderation period. There is also evidence of declining persistence in the G7 countries according to Cecchetti et al. (2007). Contrary to industrial countries, emerging economies have experienced high levels of inflation for a longer period. Some of these countries, such as Brazil, Argentina, Peru, Mexico, Israel and Turkey, have had periods of hyperinflation in the last 30 years. After the 1990s, the inflation levels started to decline in these countries, partly due to the important changes in the conduct of their macroeconomic policies. However, it is not clear if the inflation decrease has been accompanied by a reduction of their inflationary persistence (Oliveira and Petrassi, 2014). Piazza et al., (2018) highlighted that inflation persistence can change for a number of reasons. For instance, from a new Keynesian Phillips curve, one can list various factors that may produce persistence: (i) dependence of inflation on its own past (intrinsic persistence, such as indexation by price-setters); (ii) inertial inflation expectations (e.g., due to agents' perceived reaction function of the policymaker to price or output shocks); and (iii) persistent fluctuations in the determinants of inflation (extrinsic persistence, like marginal costs or output gap).

There are different methods available in the literature to estimate inflation persistence in Ghana and across different countries. Among them, the simplest method is to regress inflation by its own lagging order and that is what we call autoregressive (AR) model to calculate the sum of autoregressive coefficients. The higher the sum, the longer time it takes inflation to recover to the average level after a shock. Roache (2014) stated that a natural way to assess inflation persistence is to verify whether it is stationary (i.e., whether shocks permanently affect the level of inflation or instead fade over time). He noted that this approach assumes that the inflation rate process has no unit roots and the absolute value of the sum of autoregressive coefficients is lower than one. Methods that are more sophisticated include, for instance, the estimation of reduced-form Phillips curves, or even building structural macroeconomic models representing the inflationary dynamics based on latent factors and Kalman filtering (see Pivetta and Reis, 2007, or Rudd and Whelan, 2007).

In this paper, we tackle this subject from a different perspective. The objective of the paper is to study the persistence of Ghanaian inflation, and its main components, using quantile regression techniques. Quantile regression is a statistical method for estimating models of the conditional quantile function. Indeed, quantile regression can be viewed as a generalization of median regression. As an alternative approach, expectiles form a generalized approach to the classic mean regression. See Waltrup et al. (2015) for a good discussion of expectiles and quantile regression. The quantile regression technique allows statistical inferences in the entire conditional distribution quantile function; therefore, it is widely used in many fields these days. In recent years, a great amount of empirical applications appeared in the time-series literature based on quantile regressions, such as: Gaglianone et al. (2011); Engle and Manganelli (2004); Gaglianone and Lima (2012, 2014); Koenker and Xiao (2006); Koenker and Zhao (1996); Lima et al. (2008); Xiao (2009, 2014) among many others.

Regarding the use of quantile autoregression for analyzing inflation, Cicek and Akar (2013) for Turkey and Wolters and Tillmann (2015) for the United States, Maia and Cribari-Neto (2006) for Brazil are recent examples. In terms of Ghanaian inflation, Mavikela et al., (2018) analyzes the dynamic relationship between inflation and economic growth for South Africa and Ghana using quarterly empirical data collected from 2001 to 2016. They found that the inflationary dynamics are not uniform across different conditional quantiles.

To describe the dynamics of inflation, in this paper we use the quantile autoregression model (QAR), proposed by Koenker and Xiao (2002, 2004, 2006), in which the autoregressive coefficient may assume different values in distinct quantiles, allowing testing the asymmetry hypothesis for the inflation dynamics. Also, the model allows investigating the existence of quantile-specific unit roots. In other words, the model enables us to identify locally non-stationary dynamics while remaining compatible with a global stationarity hypothesis of the investigated series. Similarly, the model can be reformulated in a more conventional random coefficient notation, in order to reveal the periods of local non-stationarity. Another advantage of this technique is the estimation method, which does not require knowledge of the innovation process distribution, making this approach robust against poorly specified models.

In this paper, we focus on the persistence of Ghana's inflation based on QAR model proposed by Koenker and Xiao (2006). We study the monthly year-on-year Ghana consumer price index (CPI) from January 2000 to July 2019. To explore possible differences in disaggregated inflation dynamics, we investigate the two main components of the headline inflation (Food and non-food prices). Our data differ from other researches by using a newest dataset which contains almost 20 years of data (235 observations).

Data and Methodology

The study is focused on the monthly year-on-year inflation in Ghana, which is a consumer price index (CPI) used to calculate inflation target. The purpose of the study is to estimate the QAR (p) model for the monthly headline inflation (overall index) as well as its two main components: (1) food prices and (2) non-food prices. We also attempt to investigate the causality between overall inflation with its components using Granger Causality test.

The data sample periods range from January 2000 to July 2019 (235 observations) obtained from Ghana Statistical Service website (www.statsghana.gov.gh). The statistical software employed in this study are E-views and R.

Quantile Autoregression (QAR) model

In this section, we briefly describe the quantile autoregression (QAR) model approach introduced and discussed by Koenker and Xiao (2002, 2004, 2006). The technique allows direct exploration of how past information set impacts a time series conditional distribution and allows exploring of a series' unit root characteristics across different quantiles. In this paper, we employ the quantile autoregression (QAR) model to possibly carry out a unit root test at each quantile and separate non-stationary observations from stationary ones.

We first define the *p-th* order autoregressive process as follows,

$$y_t = \alpha_0(U_t) + \alpha_1(U_{t-1})y_{t-1} + \cdots + \alpha_p(U_{t-p})y_{t-p}, \quad t = 1,2,\ldots,n. \tag{1}$$

Where $y_t = \pi_t - \mu$, π_t and μ represent the inflation rates and its long-run equilibrium values respectively and $\alpha_j's$ are unknown functions $[0,1] \to \mathbb{R}$ to be estimated. According to Koenker and Xiao (2004) if the right part of the equation (1) is monotonically increasing with U_t, then the $\tau - th$ conditional quantile function of y_t, which is conditional on its past information set I_{t-1} can be written as a linear function of y_{t-1} with the lagged values of y_t as follows:

$$Q_{yt}(\tau | y_{t-1}, \ldots, y_{t-p}) = \alpha_0(\tau) + \alpha_1(\tau)y_{t-1} + \cdots + \alpha_p(\tau)y_{t-p} = Q_{yt}(\tau|F_{t-1}) = x_t'\alpha(\tau) \tag{2}$$

where $x_t' = (1, y_{t-1}, \ldots, y_{t-p})'$ and $\alpha(\tau) = (\alpha_0(\tau), \alpha_1(\tau), \ldots, \alpha_{p+1}(\tau))'$, with $\alpha_0(\tau)$ representing the τ^{th} quantile of u_t. The $\alpha_1(\tau)$ measures the speed of mean reversion of y_t within each quantile. The autoregression estimation involves the solution to the problem:

$$\underset{\{\alpha \in R^{p+1}\}}{min} \sum_{t=1}^{n} \rho_\tau(y_t - x_t'\alpha) \tag{3}$$

where the ρ_τ is well-defined by Koenker and Bassett (1978) as:

$$\rho_\tau(u) = \begin{cases} \tau u, u \geq 0 \\ (\tau - I)u, \ \ u < 0 \end{cases} \tag{4}$$

Autoregressive order choice

Equation (1) gives our *p*-th order quantile autoregression model. We now discuss how to choose the optimal lag length *p*. We follow Koenker and Machado (1999) in testing for the null hypothesis of exclusion for the p-th control variable $\alpha_p(\tau)$ as it follows:

$$H_0: \alpha_p(\tau) = 0, \qquad \text{for all } \tau \in \Gamma, \tag{5}$$

where Γ is some (discrete) index set Γ ⊂ (0,1). Let $\hat{\alpha}(\tau)$ denote the minimizer of

$$\hat{V}(\tau) = \min_{\{\alpha \in \mathbb{R}^p\}} \sum \rho_\tau(y_t - x_{1t}'\alpha),$$

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where $x'_{1t} = (1, y_{t-1}, \dots, y_{t-(p-1)})'$. Thus, $\hat{\alpha}(\tau)$ and $\tilde{\alpha}(\tau)$ denote the unrestricted and restricted quantile regression estimates. Koenker and Machado (1999) state that one can test the null hypothesis (5) using a related version of the likelihood process for quantile regression for several quantiles. Suppose that the $\{U_t\}$ are i.i.d. but drawn from some distribution F. The LR statistics at a fixed quantile τ is derived, under some regularity conditions as follows:

$$L_n(\tau) = \frac{2\left(\tilde{V}(\tau) - \hat{V}(\tau)\right)}{\tau(1-\tau)s(\tau)}, \tag{6}$$

where $s(\tau)$ is the sparsity function, defined by:

$$s(\tau) = \frac{1}{f(F^{-1}(\tau))}.$$

The sparsity function, also known as the "quantile-density function", plays the role of a nuisance parameter. To carry out a joint test about the significance of the *p*-th autoregressive coefficient for the set of quantiles Γ, Koenker and Machado (1999) suggest using the Kolmogorov-Smirnov type test statistics:

$$\sup_{\tau \in \Gamma} L_n(\tau).$$

We, therefore, show that under the null hypothesis (5):

$$\sup_{\tau \in \Gamma} L_n(\tau) \rightsquigarrow \sup_{\tau \in \Gamma} Q_1^2(\tau),$$

where $Q_1(\cdot)$ is a Bassel process of order 1. Critical values for $sup\, Q_q^2(\cdot)$ are extensively tabled in Andrews (1993).

Global Stationarity

An approach for testing the unit root property is to examine it over a range of quantiles $\tau \in \Gamma$, instead of focusing only on a selected quantile τ, by using a Kolmogorov-Smirnov (KS) type test based on the regression quantile process for $\tau \in \Gamma$. In this sense, Koenker and Xiao (2006) proposed the following quantile regression-based statistics for testing the null of a unit root:

$$QKS = \sup_{\tau \in \Gamma} |U_n(\tau)|, \tag{7}$$

where $U_n(\tau)$ is the coefficient based statistics given by:

$$U_n(\tau) = n(\hat{\alpha}_1(\tau) - 1.$$

Koenker and Xiao (2004) suggest the approximation of the limiting distribution of (8) under the null hypothesis by using the autoregressive bootstrap (ARB). An alternative way is to approximate the distribution under the null using the residual-based block bootstrap procedure (RBB). The advantages of the RBB over ARB are documented in

Lima and Sampaio (2005). In this paper, we conduct usual unit root tests (e.g. ADF) to check for global stationarity.

It is worth stating that the quantile regression process is robust in distributional assumptions, a property that is inherited from the robustness of the ordinary sample quantiles. Also, it is not the extent of the dependent variable that matters in quantile regression, but its location related to the estimated hyperplane. As a result, the estimated coefficients are less sensitive to outlier observations than the standard OLS estimator. This superiority over OLS estimator is, in fact, common to any M-estimator.

Empirical Results

Figure 1. displays the dynamic trends of the headline monthly rate since January 2000. We have observed a significant variation in Ghana's headline inflation rate for the past 20 years. Also, Figure 3.2 shows the headline (overall index) inflation rate per annum (12 months) since 2000 as measured by the Ghana statistical service (GSS) which reveals the more current episodes, after the adoption of the 2002 inflation-targeting framework by Bank of Ghana. We observe that the overall monthly year-on-year inflation series displays a descending trend which fluctuate in excess of the period of study (2000 to 2019). The variation in the overall inflation series indicates that the mean and the variance of the inflation rates are not constant in excess of time.

Table 1. shows the descriptive statistics for the headline (overall index) as well as its components such as food and non-food prices. The results reveal that, the average overall inflation rate per month and 12-months is 1.29% and 16.99% respectively. In addition, the distribution of the overall inflation rate time series and its components shows a very high kurtosis values and all of them apparently skewed to the right. It can be seen evidently that, among the components, non-food indices are the most unpredictable since they present higher average inflation compared to food prices. Also, considering the monthly inflation rates for overall inflation besides its components as shown in Figure 3.3, we found that the data for overall inflation along with its components are affected by the period of disinflation and a spike of inflation in 2003. We can infer that this inflationary period was as a result of the too much increase in money supply which is solitary by improved real sector activities or increase productivities in the economy.

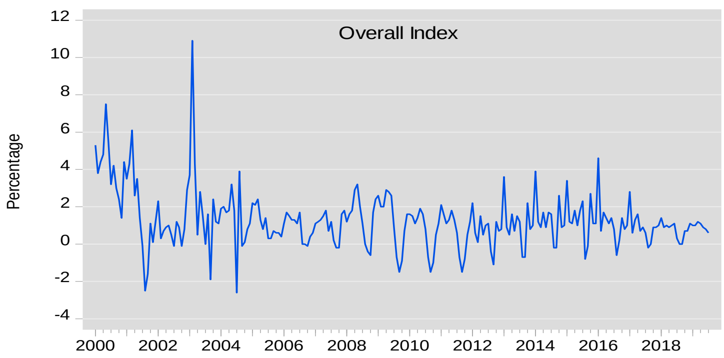

Figure 1 Headline Inflation rate (% per months)

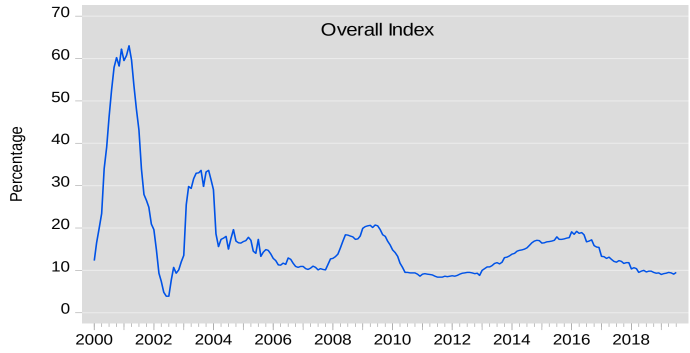

Figure 2. Overall Inflation rate (% per 12months)

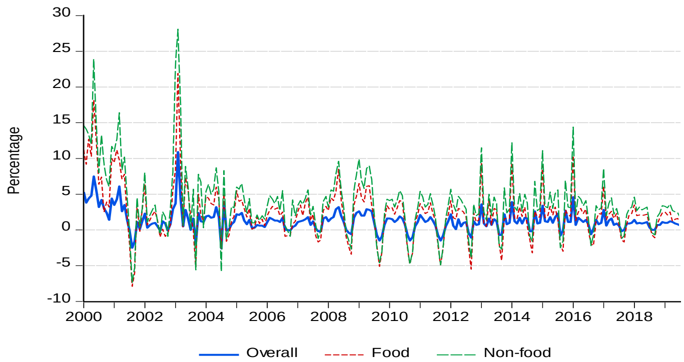

Figure 3. Disaggregate Inflation rate (% per months)

Table 1. Descriptive Statistics for Inflation and its components (% per month)

Inflation	Mean	Median	Std. Dev	Maximum	Minimum	Skewness	Kurtosis
	% per month						
Overall Index	1.29	1.10	1.53	10.90	-2.60	1.61	10.36
Food Index	1.08	1.00	2.26	11.00	-5.40	0.81	6.03
Non-Food Index	1.48	1.10	1.60	14.70	-3.20	3.32	23.95
% per 12-months							
Overall Index	16.99	13.80	11.25	63.00	3.90	2.49	9.32
Food Index	14.11	8.50	14.76	76.80	0.40	2.74	10.38
Non-Food Index	19.10	15.70	9.66	49.40	7.80	1.58	4.93

Table 2. shows the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests results to further investigate for the non-stationarity of the overall inflation rates and its components, food and non-food index for both monthly and 12-month time series. The ADF test indicate that, the null hypothesis of unit root is rejected across the respective inflation series for a 1% significance level for both

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monthly and 12-month inflation rate (apart from overall index and non-food index, 12 months, where the null hypothesis is not rejected). Similarly, we fail to reject the null hypothesis of stationarity in all cases for the KPSS test.

Table 2. Unit Root test for monthly and 12-month time series

Inflation	Monthly		12 months	
	ADF	KPSS	ADF	KPSS
Overall Index	-7.31	0.18	-3.10	0.18
Food Index	-5.73	0.14	-4.49	0.17
Non-Food Index	-12.30	0.15	-2.57	0.15

Notes: Critical values (1%): ADF (intercept) (−3.46) and KPSS (intercept) (0.74). ADF (intercept+trend) (−4.00) and KPSS (intercept+trend) (0.22). Equations for all the series include intercept and Trend.

Table 3. Estimated QAR (1) and AR(1) of Overall Inflation

τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	AR(1)
$\hat{\alpha}_0(\tau)$	-0.58* (0.000)	-0.14 (0.224)	0.20*** (0.07)	0.44* (0.000)	0.56* (0.000)	0.70* (0.000)	0.93* (0.000)	1.21* (0.000)	1.89* (0.000)	0.63* (0.000)
Std.Error	0.172	0.119	0.110	0.073	0.077	0.088	0.098	0.182	0.312	0.112
$\hat{\alpha}_1(\tau)$	0.41* (0.000)	0.41* (0.000)	0.42* (0.000)	0.42* (0.000)	0.49* (0.000)	0.53* (0.000)	0.54* (0.000)	0.56* (0.000)	0.63* (0.000)	0.50* (0.000)
Std.Error	0.099	0.071	0.062	0.053	0.055	0.056	0.058	0.109	0.186	0.056
Half-lives(HLs)	0.78	0.78	0.80	0.80	0.97	1.09	1.12	1.20	1.50	

Note: *statistical significance at 1% level, **statistical significance at 5% level, ***statistical significance at 10% level. Values in brackets are p-values.

In this analysis, we consider the simplest QAR (1) model $Q_{y_t}(\tau|y_{t-1}) = \alpha_0(\tau) + \alpha_1(\tau)y_{t-1}$. Table 3.3 shows the point estimates regression of overall inflation for a discrete grid of quantiles τ and the AR (1) model. We first of all consider the behavior of the overall inflation rate in each specific quantile by observing the estimated value for $\hat{\alpha}_0(\tau)$ and $\hat{\alpha}_1(\tau)$ (the intercept and the autoregressive coefficient respectively). The estimated $\hat{\alpha}_0(\tau)$ shows the magnitude of the observed shocked within the quantile τ that affects the inflation rates. The positive (negative) indication of $\hat{\alpha}_0(\tau)$ shows a positive (negative) shock as a result of loosened (tightened) monetary policy or an economic boom (recession). Also, we observed that the sizes of the shocks are significantly different across the grid of quantiles τ. The shocks for the overall inflation rate are within the range from -0.58 to 1.89 indicating that the inflation series moves away from its long-run symmetry level of about 1.88 units. However, the estimated values of $\hat{\alpha}_1(\tau)$ across the grid of quantiles τ are significantly far below unity with very small p-values that reject the null of hypothesis of unit root. This indicate that the overall inflation rate of Ghana displays mean reversion behavior.

We also include in our analysis the calculation of the half-life (HLs) ($HLs = \ln(0.5)/\ln(\hat{\alpha}_1(\tau))$) in each quantile based on the estimated values of $\hat{\alpha}_1(\tau)$. The HLs are quite small below the median quantile (50%) and quite larger above the median quantile (50%). For instance, in the lower quantile (10%), the HLs are small suggesting that when hit by a larger negative shock, the inflation rates can return to their long-run symmetry very quickly. In contrast, in the highest quantile (90%), the HLs are high suggesting that inflation rates do not tend to revert to its long-run symmetry. From the results, we established that the regression parameter estimates of the QAR model are unrelated at different quantiles, suggesting that the Ghana inflation rate has irregular characteristics at different quantiles in its conditional distribution. Similar results displaying the point quantile regression estimates for Food and Non-food inflation series are found in Table 4.

Again, we compare the regression coefficient estimates of the ordinary least squares (OLS) and the quantile autoregression methods for overall inflation series and its components (food and non-food series) by using a finer segmentation of quantiles ($\tau \in [0.01, 0.99]$) with a steps of 0.01 in Figure 4, Figure 5 and Figure 6. The solid red lines and two dashed red lines show the estimated intercept and regression coefficients of OLS and their 95% confidence intervals respectively. The dotted line and the shaded part show the estimated intercept ($\hat{\alpha}_0(\tau)$)and regression coefficients ($\hat{\alpha}_1(\tau)$) of QAR (1) and their 95% confidence intervals at [0.01, 0.99] by steps of 0.01 respectively. We can observe that there is a significant difference below and above OLS suggesting QAR model better than simple OLS estimates.

Table 4. Estimated QAR(1) and AR(1)

Food Inflation										
τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	AR(1)
$\hat{\alpha}_0(\tau)$	-1.79* (0.000)	-0.97* (0.000)	-0.25 (0.233)	0.32** (0.022)	0.53* (0.000)	0.77* (0.000)	1.07* (0.000)	1.50* (0.000)	2.51* (0.000)	0.44* (0.000)
Std.Error	0.211	0.223	0.209	0.137	0.101	0.081	0.115	0.153	0.553	0.133
$\hat{\alpha}_1(\tau)$	0.53* (0.000)	0.56* (0.000)	0.54* (0.000)	0.49* (0.000)	0.52* (0.000)	0.53* (0.000)	0.53* (0.000)	0.50* (0.000)	0.61** (0.009)	0.57* (0.000)
Std.Error	0.092	0.088	0.057	0.054	0.043	0.038	0.040	0.073	0.231	0.053
Half-lives(HLs)	1.09	1.20	1.12	0.97	1.06	1.09	1.09	1.00	1.40	
Non-Food Inflation										
τ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	AR(1)
$\hat{\alpha}_0(\tau)$	0.30** (0.012)	0.58* (0.000)	0.76* (0.000)	0.85* (0.000)	0.88* (0.000)	0.95* (0.000)	1.15* (0.000)	1.58* (0.000)	1.98* (0.000)	1.11* (0.000)
Std.Error	0.118	0.077	0.070	0.066	0.090	0.077	0.125	0.146	0.440	0.139
$\hat{\alpha}_1(\tau)$	0.00 (1.000)	0.03 (0.614)	0.03 (0.476)	0.07 (0.313)	0.21*** (0.012)	0.28* (0.000)	0.34* (0.000)	0.37** (0.003)	0.58*** (0.031)	0.25* (0.000)
Std.Error	0.083	0.050	0.045	0.067	0.081	0.053	0.088	0.125	0.267	0.064
Half-lives (HLs)	0.00	0.20	0.20	0.26	0.44	0.54	0.64	0.70	1.27	

Note: *statistical significance at 1% level, **statistical significance at 5% level, ***statistical significance at 10% level. Values in brackets are p-values.

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Table 5. shows the results of the estimated AR (6) model (for comparison). However, we find that there is no significant difference between the fitted and the actual series for overall inflation and its components (food and non-food) as shown in Appendix 2.

The CUSUM plot was used to check the stability of the long-run parameters together with the short-run association of the overall inflation series. The plot indicates a significant shift in the parameters of the short-run regression model. Precisely, the recursive estimation of the coefficients and the residuals which also check the parameter constancy of the model shows instability in the coefficient with the standard error interval shrinking quickly. Correspondingly, the recursive residual tests also confirm parameter shifts by means of the recursive residuals fluctuating extensively within the critical bounds. As a result, the model displays parameter instability with indication of major volatility since 2000 as shown in Appendix 1.

Table 5. Estimated AR(6) for Overall inflation series and its components (Food and Non-food)

	Intercept	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)
Overall	0.649* (0.136) (0.000)	0.417* (0.067) (0.000)	0.032 (0.071) (0.653)	0.203** (0.069) (0.004)	-0.263* (0.069) (0.000)	-0.009 (0.071) (0.890)	0.066 (0.063) (0.293)
Food	0.665* (0.143) (0.000)	0.563* (0.066) (0.000)	-0.086 (0.073) (0.241)	0.097 (0.070) (0.170)	-0.304* (0.070) (0.000)	0.165*** (0.072) (0.024)	-0.132*** (0.061) (0.033)
Non-Food	0.815* (0.194) (0.000)	0.110** (0.067) (0.003)	0.152*** (0.067) (0.025)	0.075 (0.068) (0.268)	-0.053 (0.067) (0.430)	-0.043 (0.066) (0.520)	0.096 (0.065) (0.142)

Note: *statistical significance at 1% level, **statistical significance at 5% level, ***statistical significance at 10% level. Values in brackets are standard error and p-values.

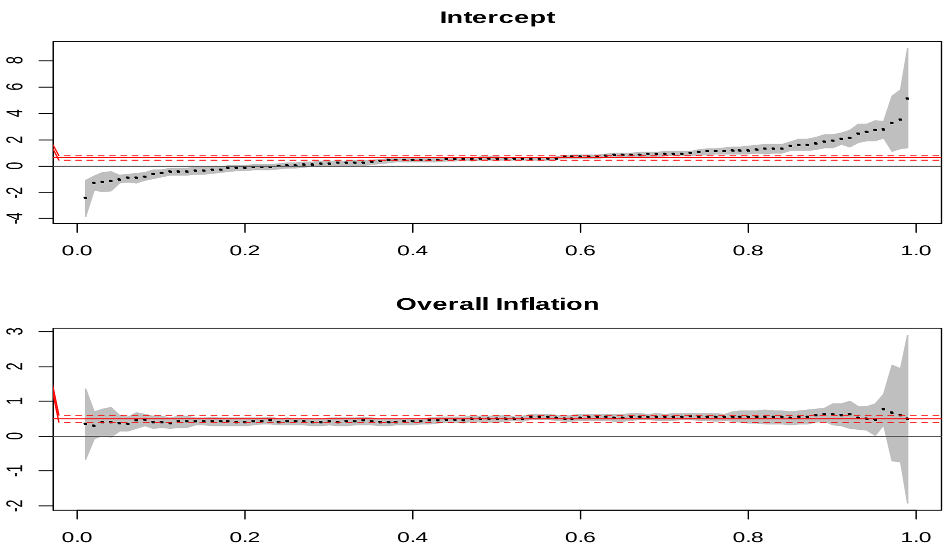

Figure 4. Estimated coefficients (Monthly Overall Inflation, 2000-2019)

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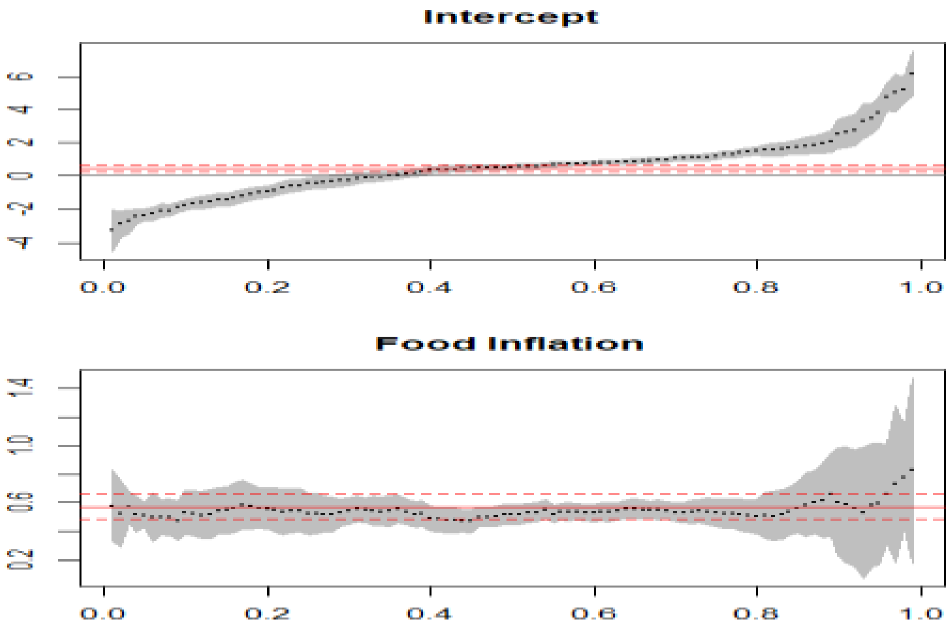


Figure 5. Estimated coefficients (Monthly Food Inflation, 2000-2019).

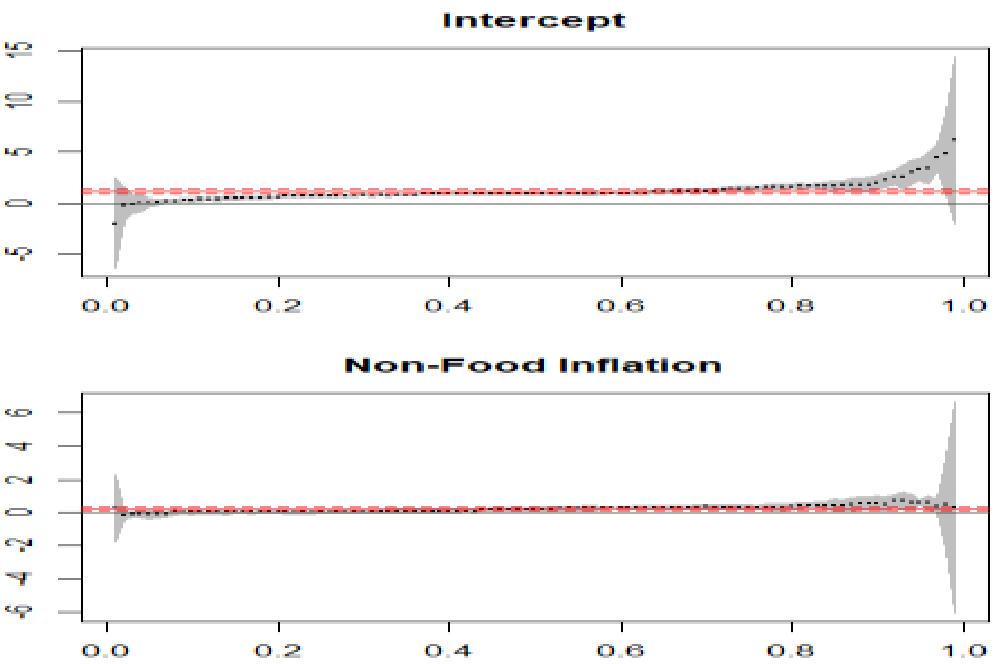


Figure 6. Estimated coefficients (Monthly Non-food Inflation, 2000-2019).

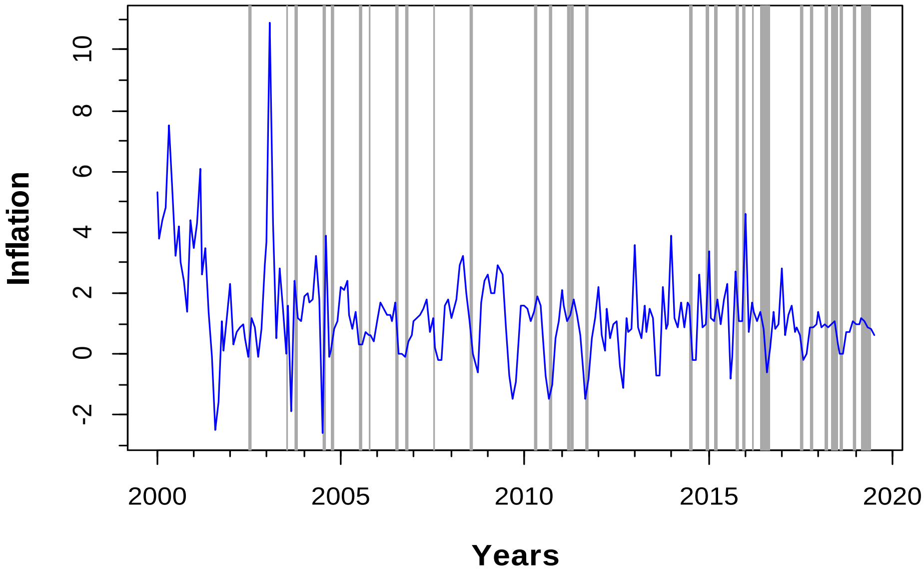


Figure 7. Plot of Inflation rate and non-stationary periods.

The blue line in figure 7. represents the overall inflation series plot, the gray areas shows that the inflation rate is non-stationary at the time, and the white areas shows that the inflation rate is stationary during the period under study.

In addition, we construct the QAR (1) model under $\tau_{crit} = 0.85$ to get the predicted value $\hat{Q}_{yt}(\tau_{crit}|y_{t-1})$ and compare it with the true value of y_t to find the non-stationary periods. We observe from Figure 7. that the number of stationary periods is more than that of the non-stationary periods. That is about 10% of the entire sample periods are non-stationary indicating that Ghana overall inflation rate is locally non-stationary nonetheless globally stationary.

The annual aggregate rate of the non-stationary periods of Ghana inflation rate throughout the sample periods further attests to the time-varying features of the Ghana inflation rate (Figure 8).

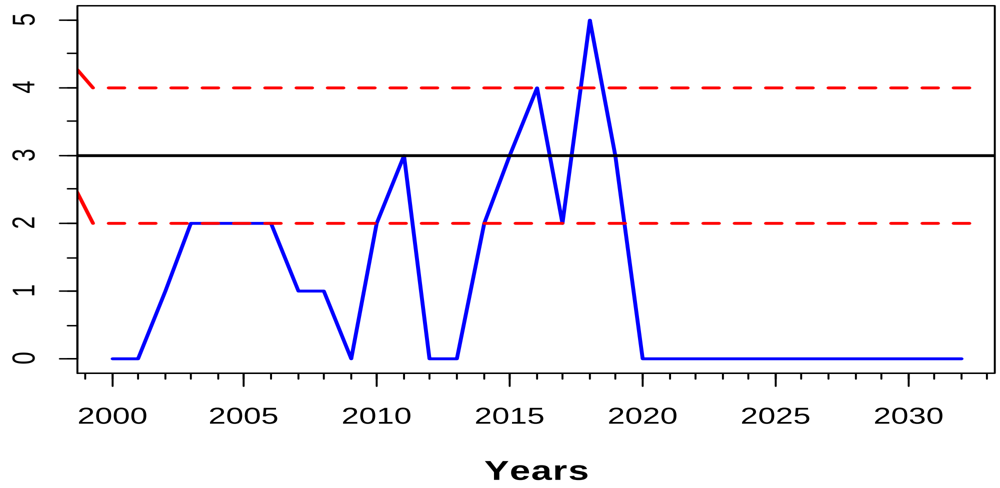


Figure 8. Plot of Twelve-month accumulated number of non-stationary periods.

The two dotted red lines represent 2 and 4 periods and the bold black line represent the 3 periods of the non-stationary episodes.

Table 6. Linear Regression Model Summary for Overall Inflation series on Food and Non-food series

Coefficients	Estimates	Std. Error	t-values	p-values
Intercept	0.242	0.048	5.013	0.000***
Food Series	0.501	0.017	29.64	0.000***
Non-food series	0.341	0.024	14.30	0.000***
F.Stats=821.85, p-value=0.000, Residual std. Error=0.541, R^2=0.876, Adjusted-R^2=0.875, AIC=1.622				

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Furthermore, we investigate if there is any relationship between overall inflation and its components (Food and Non-food inflation). The result shows that there is a significant positive relationship between overall inflation and its components, food and non-food inflation. We found that food and non-food inflation will increase overall inflation about 0.5 and 0.3 times respectively. Also, the R^2 (0.876) value indicates that food and non-food inflation series explain 87.6% of the variability of the overall inflation series (Table 6).

We however perform cointegration test by using Vector Autoregression (VAR) to determine the optimum lag order which is based on both Akaike information criterion (AIC) and Schwarz information criterion (SC). The results from Table 7. indicates that the optimal lag length established by AIC and SC are 4 and 1 respectively. We select optimum lag length of 4, the probability ratio test which depends on the maximum Eigen values of the stochastic conditions of the Johanson (1991) process was used for exploring the size of cointegrating vectors.

Table 7. VAR Lag Order selection Criteria (Endogenous Variables: Overall inflation, Food Inflation and Non-food Inflation)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1080.10	NA	2.275	9.459	9.504	9.477
1	-1023.12	111.97	1.693	9.040	9.220*	9.113*
2	-1012.13	21.302	1.664	9.023	9.338	9.150
3	-996.88	29.166	1.576	8.968	9.418	9.150
4	-979.98	31.889	1.472*	8.899*	9.484	9.135
5	-977.60	4.426	1.559	8.957	9.677	9.248
6	-964.42	24.173*	1.504	8.921	9.775	9.265

*indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 8. Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical value	P-value
None*	0.291	78.993	21.132	0.000***
At most 1*	0.174	44.067	14.265	0.000***
At most 2*	0.134	32.976	3.8414	0.000***

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
*denotes rejection of the hypothesis at 0.05 level
**Mackinnon-Haug-Michelis (1999) p-values

The Unrestricted Cointegration Rank Test (Table 8) presents the results for the cointegrating test. The result shows that there are two (2) cointegrating vectors at 0.05 level of significance. The null hypothesis of zero (none) cointegrating vector, at most one (1), and at most two (2) cointegrating vectors were all rejected against their respective alternative hypothesis. This indicates that the model identified two (2) cointegrating vectors.

Table 9. ADF-Fisher Chi-square Test for the stationarity of the residuals/error using

Variable	None	Constant	Constant and Trend
Error/Residuals	44.60	116.26	155.40
P-value	0.000	0.000	0.000

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

We use the ADF test to investigate the stationarity of the residuals obtained from the cointegration regression analysis of the overall inflation series on its components (food and non-food series). The result shows that the residual term is stationary with trend and intercept at 0.01 level of significance (Table 9).

In order to observe the linear causality and the direction of the relationship between the variables under study, we perform Granger (1996) causality test. The results of the Granger causality test at lag 4 is presented in Table 10. We observe that there is a bidirectional connection between overall inflation series and its components (food and non-food series).

Table 10. Pairwise Granger Causality Tests (2000-2019, Lags: 4)

Null Hypothesis:	Obs	F-Statistic	P-values
Non-Food does not Granger Cause Overall Overall does not Granger Cause Non-Food	231	2.871 6.072	0.0239 0.0001
Food does not Granger Cause Overall Overall does not Granger Cause Food	231	5.026 3.756	0.0007 0.0056
Food does not Granger Cause Non-Food Non-Food does not Granger Cause Food	231	3.318 3.811	0.0115 0.0051

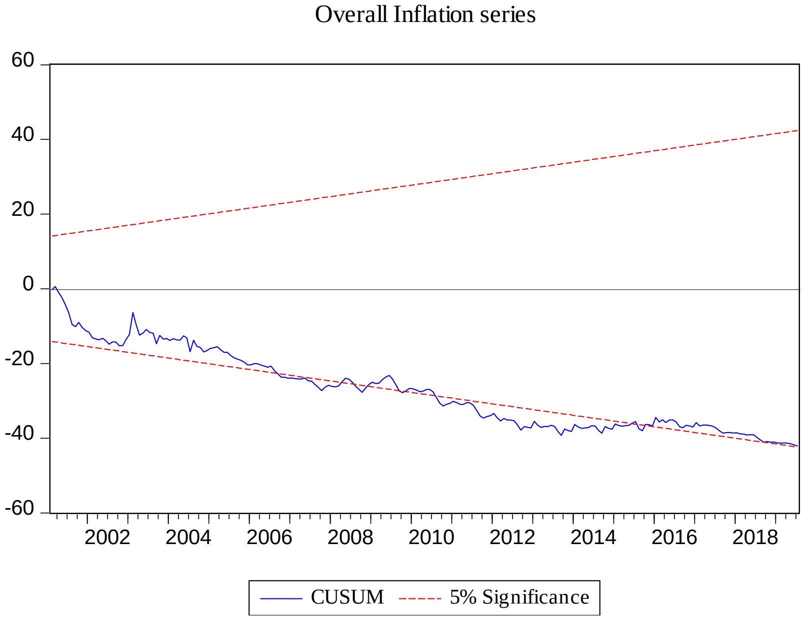
Conclusions

The purpose of this study is to investigate the dynamics of monthly year-on-year inflation in Ghana as well as possible differences in its components (food and non-food inflation) using quantile autoregressive model proposed by Koenker and Xiao (2006). We attempt to estimate the QAR (p) model for the monthly headline inflation (overall index) as well as its two main components: (1) food prices and (2) non-food prices. Again, we try to examine the causality between overall inflation with its components using Granger Causality test.

The results from the Augmented Dickey-Fuller (ADF) test indicates that overall inflation rate and its components (food and non-food inflation rates) are stationary in Ghana. Also, we consider the behavior of the overall inflation rate in each specific quantile which reveals that the sizes of the shocks are significantly different across the grid of quantiles. We observe negative shocks at lower quantiles as a result of tightened monetary policy or an economic recession while positive shocks are observed at higher quantile as a result of loosened monetary policy or economic boom. That is the shocks for the overall inflation rate are within the range of -0.58 to 1.88 units suggesting that inflation series moves away from its long-run symmetry level of about 1.88units. However, the autoregressive coefficients for the overall inflation rate across the grid of quantile are significantly far below unity symptomatic of displaying a mean reversion behavior. Conversely, we established that the regression parameter estimates of the quantile autoregression model are unrelated at different quantiles, signifying that Ghana inflation rate has irregular characteristics at different quantiles in its conditional distribution. In comparing the intercept terms and the regression coefficients of both ordinary least squares (OLS) method and quantile autoregressive (QAR) model respectively, we concluded that QAR model has more power compared to OLS method. That is QAR model can well reveal the dynamic process of overall inflation series. Ghana overall inflation rate has low persistence characteristics both in the middle and the end of the conditional distribution. That is the QAR model used to calculate the inflation persistence coefficient is far below one (1). Correspondingly, Ghana inflation has lower persistence when at both lower and higher quantiles in the inflation conditional distribution suggesting symmetric characteristics behavior of Ghana inflation rate. We found that Ghana inflation rate is locally non-stationary but globally stationary with a time-varying characteristics.

The stability check for the long-run and the short-run association of the overall inflation rate shows that Ghana overall inflation rate displays parameter instability. We observe a significant positive relationship between overall inflation and its components (food and non-food) in Ghana. Finally, the Granger causality test reveals a bidirectional relationship between Ghana overall inflation rate and its components (food and non-food inflation).

Appendix 1a: Tests on parameter stability (CUSUM)



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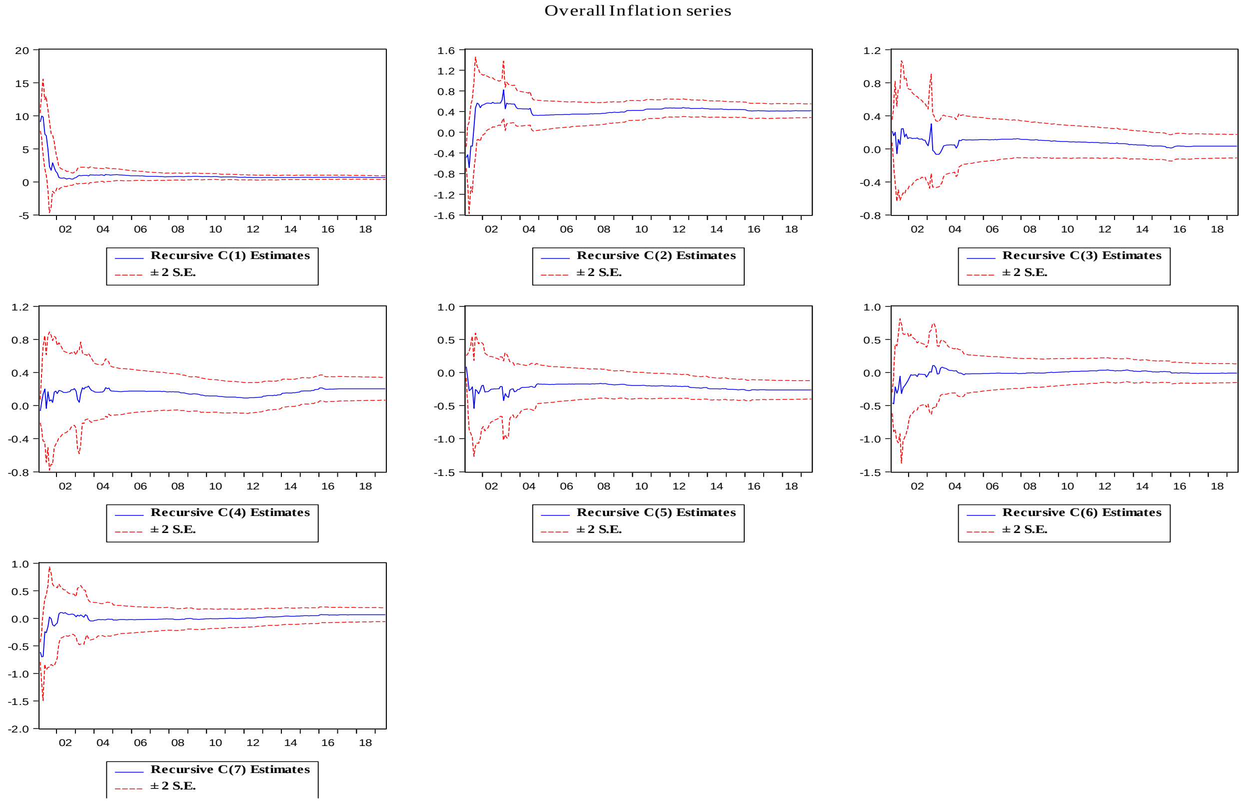
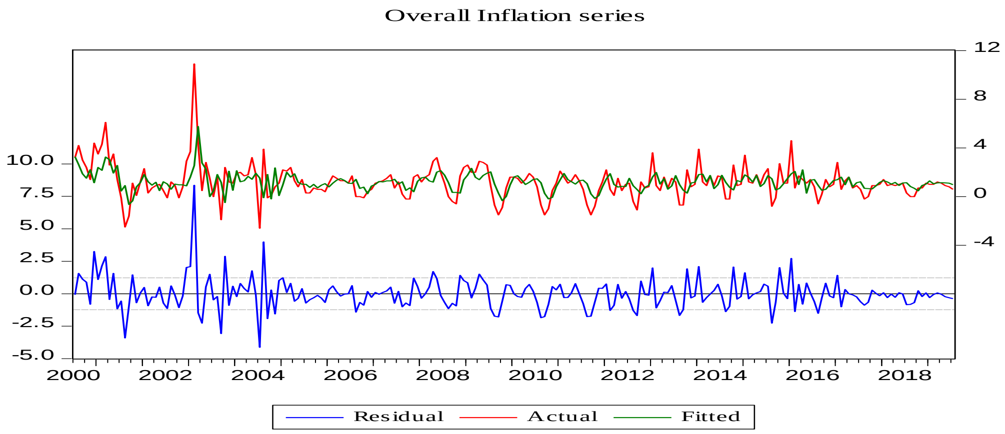
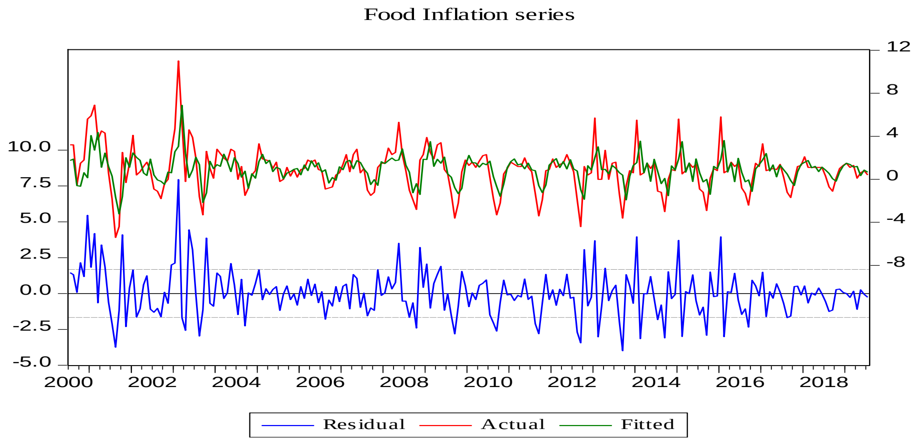
Appendix 1b: Tests on parameter stability (Recursive coefficients for Overall Inflation seri



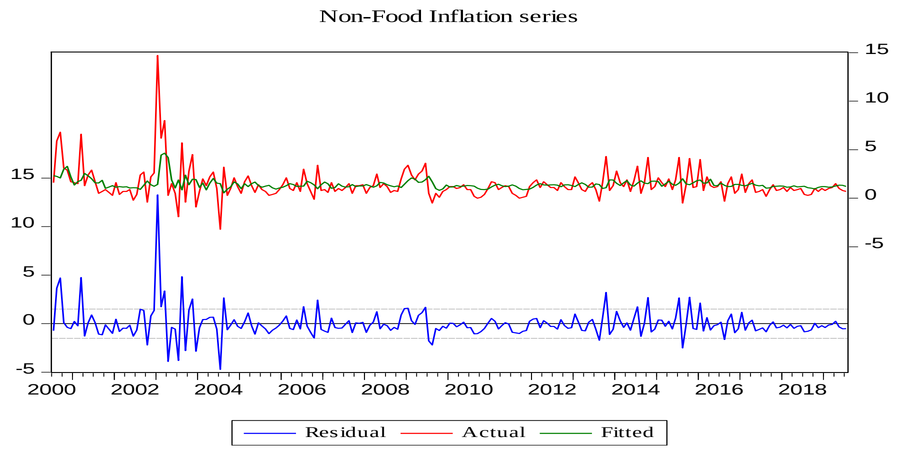
Appendix 2a Residual, Actual and fitted plot for Monthly Overall Inflation (2000-2019).



Appendix 2b Residual, Actual and fitted plot for Monthly Food Inflation (2000-2019).



Appendix 2c Residual, Actual and fitted plot for Monthly Non-food Inflation (2000-2019).



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