On the inflation and inflation uncertainty nexus: Evidence from quantile regression

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Abstract

This study empirically investigates the link between inflation and its variability in Ghana through quantile regression analysis. Utilizing monthly time series data spanning five decades, we find robust evidence to support the hypotheses that inflation drives inflation uncertainty and vice versa. In contrast to the conditional mean approach, results from quantile estimates suggest that the impact of either inflation uncertainty on inflation or the reverse differs significantly in magnitude with stronger impact observed for the higher tail of the distribution of the outcome variable. Implications of our results for economic policy are analysed.

JEL classification: C21; E31; E64

Keywords: Inflation; Inflation uncertainty; Quantile regression; GARCH; Ghana

1. Introduction

The level of inflation, underpinned by its drivers, is seen as one of the most important indicators of general economic performance with implication on almost all sectors of an economy independent of the level of development or geography. There is wide consensus among economists and policymakers that ensuring stability in the general price is vital to the health of the economy and welfare of citizens. It is therefore no secret that economic managers all over the world face an arduous task of ensuring that inflation is stable and within growth-enhancing limits.

Often, high and unanticipated inflation rates tend to drag along with it a signal of price uncertainty to both policymakers and all other economic agents. Okun (1971) agrees that "… if there were such an economic state as steady, fully anticipated inflation, it would impose only minor social costs". However, the existence of such a state in any economy is virtually impossible. According to Okun (1971) "…adoption of a public policy designed to yield steady, fully anticipated inflation would commit the government to an impossible goal" given imperfection with economic policy-making. Therefore, government's acceptance of higher inflation rate would most likely drive expectations in such a manner to induce the general price level rising more rapidly and less steadily (Okun, 1971). It therefore follows from Okun's prognosis that how expectations are formed by economic agents about volatility and future inflation trends matter for current inflation. That is to say, Okun's main prediction is that high inflation leads to pronounced uncertainty and therefore it is imperative to assess this link in order to understand the social and economic costs of inflation (Ball and Cecchetti, 1990).

Ghana, similar to other Sub-Saharan African countries, has had often very high and volatile rates of inflation particularly in the late 1970s through to the early 1980s. Various reasons have been assigned for this trend notable among which include high public expenditure, excessive money supply growth, rapid depreciation of the domestic currency against major trading partners', external shocks, drought (in 1983) and low agricultural productivity (Marbuah, 2011). Following adoption of economic policy reforms in the early 1980s from the International

Monetary Fund (IMF) and World Bank, the economic malaise seemed to have reversed significantly with inflation rate falling from approximately 123% in 1983 to 10.3% by 1985 (see Marbuah, 2011; Adu and Marbuah, 2011 for a discussion on Ghana's inflation dynamics). Official statistics have often revealed high volatility in inflation especially in periods of high inflation and during the political-business cycle periods (i.e. elections) even though in recent times the rates have generally been low and sometimes even in single digits (partly due to the inflation targeting monetary policy framework of the central bank) compared to historical trends. It is therefore important to subject Ghana's inflation data to an application of robust analysis to ascertain whether high inflation is the one driving its variability or the converse is the case.

Ghana's chronic high inflation rates and accompanying price volatility over the past three to four decades has stifled economic progress with the business community often entangled in a climate of high uncertainty. As a result, most decisions regarding plant size expansion, investment and employment are either delayed or put on hold indefinitely. More importantly, annual inflation targets of the Central Bank of Ghana have often been missed. One of the reasons for missing inflation targets could be attributed to the lack of clear evidence on and consideration of what happens along the entire distribution of either inflation or inflation uncertainty series and its implication for monetary policy conduct. This is particularly important given that it could potentially inform policy-makers on specifically where along the inflation distribution to set its target.

The main purpose of this paper therefore is to empirically examine the link between inflation and its variability and to assess which of them drives the other. We implement this by employing variant generalized autoregressive heteroskedasticity (GARCH), exponential GARCH (EGARCH) frameworks and the standard deviation of inflation to generate three different measures of inflation uncertainty. We then use annualized monthly inflation data on Ghana over the last five decades (1963-2014) to test the Friedman-Ball and Cukierman-Meltzer hypotheses. Unlike other studies on Ghana (Barimah and Amuakwa-Mensah, 2013; Sintim-Aboagye, 2011; Sintim-Aboagye, 2013; and Oteng-Abayie and Doe, 2013), we utilize quantile regression techniques proposed by Koenker and Bassett (1978) to analyse the distributional impact of either inflation uncertainty or inflation on the other. The use of the quantile estimator is premised on its robustness in relation to outlying observations of the outcome variable. Unlike the conditional mean estimator, which is sensitive to outliers, quantile estimators have been found to be insensitive to extreme values. Further, we are able to compute the relative impact of each variable on the other at different quantiles along the distribution of the level of inflation and its variability. This gives a complete picture of how either inflation impacts inflation uncertainty or the reverse with important implication for economic policy and decision-making. We provide robust evidence via conditional mean and quantile regression estimates as well as Granger-causality tests that inflation uncertainty drives inflation and a further validation of the reverse hypothesis. Most significantly, we show that both inflation uncertainty and inflation drive each other differently in magnitude and significance at varying quantiles along each of their distributions, evidence often indiscernible when application is done through conditional mean estimation. Importantly, we find that the impacts of these phenomena are much stronger at the upper tail of the inflation and inflation variability distribution. The implication from the quantile analysis will have significant impact on assessment of the inflation-inflation uncertainty nexus for monetary, growth, and other macroeconomic policies in Ghana.

The remainder of the paper is structured as follows. Section 2 provides a brief review of both theoretical and empirical literature on inflation and inflation uncertainty nexus. We explain the methodology applied to the data in this study under Section 3. Discussion of results is carried out in Section 4. We conclude the paper with discussion of policy implications in Section 5.

2. Literature review

Theoretically, the nexus between inflation and its' uncertainty is grouped into four hypotheses; (i) the Friedman-Ball hypothesis (Friedman, 1977 and Ball, 1992), (ii) the Cukierman and Meltzer hypothesis (Cukierman and Meltzer (1986), (iii) the Pourgerami and Maskus hypothesis (Pourgerami and Maskus (1987)) and (iv)Holland hypothesis (Holland, 1995). While

Friedman-Ball hypothesis predicts causality is found to run from inflation to inflation uncertainty, Cukierman and Meltzer (1986) suggest the reverse linkage that inflation variability leads to higher inflation. "Pourgerami and Maskus" and "Holland" Hypotheses reject the harmful effect that high inflation has on predictability of prices so a negative relation between inflation and inflation uncertainty is thus postulated by these hypotheses. In contrast to Friedman-Ball Hypothesis, Pourgerami and Maskus (1987) argue that higher inflation signals economic agents to invest more in generating accurate predictions, which reduces their prediction error. Therefore, with rising inflation, agents may forecast inflation better due to the improved prediction capacity. Similarly, Holland (1995) asserts that higher inflation variability lowers inflation due to stabilization motives of policymakers. In the so-called "stabilizing Fed hypothesis", Holland assumes that stabilization tendencies of central banks increase in high inflation periods in order to reduce the welfare costs of disinflationary policies when inflation uncertainty is high.

Empirically, among the studies which make use of the GARCH model, the conclusions have been mixed. Whereas most of these studies (Fountas, 2001; Grier and Grier, 2006; Fountas and Karanasos, 2007; Thornton, 2007; Payne, 2008; Thornton, 2008; Caporale *et al.*, 2009) support the Friedman-Ball hypothesis, others affirm the Cukierman-Meltzer hypothesis (Neanidis and Sava, 2011) or both hypotheses (Ozdemir and Fisunoğlu, 2008; Mladenović, 2009; Korap, 2010; Salmanpour and Bahloli, 2011). The ARCH/GARCH model has some known limitations in the sense that it is incapable of providing reliable assessments of the inflation-uncertainty nexus. By construction, inflation uncertainty measures generated by ARCH/GARCH models are invariant to the direction of change in inflation (Wilson, 2006). Thus, these models require that all of estimated parameters are positive, and also do not restrict the effect of outliers. Due to these limitations of the GARCH models identified, some authors resort to the EGARCH model which circumvents these limitations, to examine the link between inflation and uncertainty. Among studies that utilize the EGARCH model, Hegerty (2012) find that inflation increases fuel uncertainty in Burkina Faso, Botswana, Cote d'Ivoire, Ethiopia, Gambia, Kenya, Nigeria, Niger and South Africa, while the reverse relationship only holds for Burkina Faso, Gambia, Kenya and Nigeria. In the same vein, Samimi *et al.*, (2012) using five MENA countries (Iran, Egypt, Morocco, Syria and Jordan) show that there is an asymmetric relationship between inflation and inflation uncertainty for these countries. Moreover, they establish strong evidence that inflation uncertainty display significant positive effects from inflation in these countries except for Egypt, supporting the Friedman-Ball hypothesis. Further, Chen *et al.*, (2008), used a flexible regression model with inflation uncertainty generated from a moving average standard deviation to examine the nexus between inflation and its uncertainty in four Asian countries (Hong King, South Korea, Singapore and Taiwan). Except for Hong Kong, they find significant support for the Friedman-Ball hypothesis. On the other hand, evidence was established for all countries in favour of the Cukierman-Meltzer hypothesis.

In recent times, some studies examining this relationship have made use of quantile regression analysis. Among these studies include the work of Tillmann and Wolters (2014), Çiçek and Akar (2013), Yeh *et al.*, (2011), Tsong and Lee (2011) and Fang *et al.*, (2010). Tillmann and Wolters (2014) show that structural break was persistent in all quantiles of the inflation process in the early 1980s in the US. Similarly, Çiçek and Akar (2013) reveal that there exists an asymmetric speed in inflation adjustment process across different quantiles before and after inflation targeting (IT) regime in Turkey. The results of Yeh *et al.*, (2011) suggest that positive inflation shocks have stronger impact on inflation uncertainty and this varies across quantiles. They also find that popular time series models that are evaluated for their ability to reproduce measures of uncertainty yield similar results for the relationships between inflation and inflation uncertainty. Tsong and Lee (2011) uncovered that inflation rates are not only mean-reverting but also exhibits asymmetries in their dynamic adjustments, in which large negative shocks tend to induce strong mean reversion, but large positive shocks do not. The findings of Fang *et al.*, (2010) support both Friedman-Ball and Cukierman-Meltzer hypotheses across all quantiles considered. Moreover, they find that higher quantiles in both cases lead to larger marginal effects of inflation (inflation variability) on inflation variability (inflation).

3. Methodology, model specification, inflation uncertainty and data

4.1 Methodology

In this section of the paper, we provide a brief theoretical background of the methodology adopted for modelling the impact of inflation uncertainty on inflation and the converse. We carry out this exercise by utilizing quantile regression proposed and developed by Koenker and Basset (1978) and Koenker (2005). It is widely acknowledged that much of applied econometric work is in respect of conditional moments, especially conditional mean functions (Cameron and Trivedi, 2010) as is the case with the ordinary least squares estimator (OLS). The OLS estimator or standard linear regression, even though useful in estimating the mean relationship between an outcome variable and a set of explanatory variables based on a conditional mean relation $E(Y|X)$, provides only a partial picture of this relationship (Cameron and Trivedi, 2010). Quantile regression is an extension of the classical conditional mean OLS estimator where the entire conditional distribution of the regressor on the outcome variable is estimated at different quantiles. This provides a complete picture of the estimated nexus between the outcome variable, Y, and the regressors, X, at varying points in the conditional distribution of Y. In other words, quantile regression allows for heterogeneity of parameters across different regressors (Yeh *et al.*, 2011).

The general or basic quantile regression model is specified as a linear conditional quantile function of regressors and given as follows:

$$Y = X' \quad + £ \qquad (1)$$

$$Q_{2}(Y|X = x) = x' \quad (^{2}) \text{ and } 0 < ^{2} < 1 \qquad (2)$$

where Y is the outcome variable, X is a matrix of regressors, £ is the error term with unspecified distribution, while $Q_{2}(Y|X = x)$ represent the $^{2\,th}$ quantile of Y conditional on $X = x$. It is assumed, by equation (2) that the error term, £, satisfies the quantile restriction $Q_{2}(£|X = x) = 0$. The $^{2\,th}$ quantile estimator $\widehat{\ }_{2}$ is found by solving the following minimization problem over $_{2}$:

$$Q(\beta_\tau) = \min_{\beta \in \Re^K} \left[\sum_{t \in \{t: Y \geq X'\beta\}} \tau \left| Y - X'\beta_\tau \right| + \sum_{t \in \{t: Y < X'\beta\}} (1-\tau) \left| Y - X'\beta_\tau \right| \right] \tag{3}$$

Equation (3) implies that the quantile regression function is a weighted sum of the absolute value of the residuals (Yeh *et al.*, 2011). If we set $\tau = 0.5$ (i.e. symmetric weights for the special median case), then the procedure leads to the estimator that minimizes the sum of absolute deviations $\sum_t \left| Y - X'\beta_{0.5} \right|$, also known as the median regression or least absolute deviation (LAD) or absolute error estimator (Koenker and Basset, 1978; Cameron and Trivedi, 2010; Yeh *et al.*, 2011). By increasing τ from 0 to 1, one is able to trace the entire distribution of Y conditional on X thus giving a complete view or picture of the impact of the explanatory variable on the outcome variable. One other key attractive attribute of the quantile regression estimator is that unlike the OLS estimator, is its robustness to the presence of outliers in the dependent variable (see Koenker and Basset, 1978; Koenker and Hallock, 2001; Koenker, 2005 for more details). Many of the studies, including those on Ghana (Barimah and Amuakwa-Mensah, 2013; Oteng-Abayie and Doe, 2013) which modelled whether inflation uncertainty drives inflation or the reverse have often ignored exploring the impact of the entire distribution of the regressor conditional on the regressand with much emphasis placed on finding conditional mean estimates. To the best of our knowledge, our paper is the first and only study that tests these two hypotheses by utilizing the quantile regression techniques in order to understanding the relative distributional effect of inflation uncertainty on inflation dynamics and the converse in the case of Ghana. The results of this analysis will prove invaluable to monetary policy conduct as the economic managers strive to tame recent rising prices within sustainable ranges.

4.2 Model specification

We examine the two hypotheses by assuming that the τ^{th} quantile of the conditional distribution of the outcome variable inflation (inflation uncertainty) is linear in the explanatory variable, inflation uncertainty (inflation). Following Yeh *et al.*, (2011), we specify the following conditional quantile regression models to explore the inflation and inflation uncertainty nexus in either direction:

$$\text{®}_t = \text{¤}_2 + \ {}_2\text{®}_t^{unc} + \text{£}_2 \tag{4}$$

$$\text{®}_t^{unc} = \sim_2 + \cdot\ {}_2\text{®}_t + {}^3{}_2 \tag{5}$$

where ® and ®^{unc} represent inflation and inflation uncertainty, respectively. $\sim_2$, ¤_2, $\cdot_2$ and $_2$ denote unknown parameters to be estimated for different quantile values (^{2}), £_2 and $^3{}_2$ are the usual disturbance/error terms; t represent time subscript. According to theory, we hypothesize a positive impact of inflation uncertainty on inflation and inflation on inflation uncertainty. In the empirical estimation, we vary the quantile value (^{2}) from 0 to 1 in order to trace the entire distribution of either inflation or inflation uncertainty as a dependent variable conditional on the other to test the hypotheses.

4.3 Measuring inflation uncertainty

We use three measures of inflation uncertainty or variability in our paper. The first variability measure follows Yeh *et al.*, (2011) and others where inflation uncertainly is derived from the standard deviation of the inflation rate (®_{STD}^{unc}). Secondly, following the work of Engle (1982), the autoregressive conditional heteroskedasticity (ARCH) class of time series models including the generalized ARCH (GARCH) model, has been used extensively to generate inflation uncertainty and for testing these hypotheses. Its attractiveness stems from its ability to generate direct and time-varying measures of inflation uncertainty (Wilson, 2006). We adopt this approach to generate our second measure of inflation variability. The general specification of the GARCH (p, q) model (i.e. GARCH-in-mean equation) of inflation which follows an m^{th} order autoregressive (AR) process for the conditional mean to measure inflation uncertainty is given by:

$$\text{®}_t = \text{«}_0 + \sum_{i=1}^{m} \ {}_i\text{®}_{t-i} + \text{£}_t, \qquad \text{£}_t \sim N(0, \text{¢}^2) \tag{6}$$

$$\text{¢}_t^2 = \mu_0 + \sum_{i=1}^{p} \text{a}_i \text{¢}_{t-i}^2 + \sum_{j=1}^{q} \ddot{}_j \text{£}_{t-j}^2 \tag{7}$$

where ®_t denotes the rate of inflation at time t and £_t is the shock to inflation at the time t assumed to follow a normal distribution with a time-varying conditional variance ¢^2. The conditional variance equation is specified as a linear function of past squared inflation surprises or shocks (i.e. the ARCH term) and the previous variances (i.e. the GARCH term). The estimated conditional variance is what is used as a measure of inflation uncertainty because it constitutes a direct, time varying measure of inflation volatility (Wilson, 2006). We use inflation uncertainty derived from an AR(3)-GARCH(1, 1) proposed by Bollerslev (1986) for our main results. Our choice of model specification is determined by the Akaike information criteria (AIC). For a positive conditional variance with a unit probability, it is sufficient to have $\mu_o > 0$, $\text{a} > 0$ and $\ddot{} > 0$ for $i = 1,..., p$ and $j = 1,..., q$. The GARCH(p, q) is (weakly) stationary if and only if $\sum_{i=1}^{p} \text{a}_i + \sum_{j=1}^{q} \ddot{}_j < 0$. The GARCH model imposes a restriction on the parameters such that it enforces symmetric response of volatility to both positive and negative shocks. Thus, a positive inflation shock increases the likelihood of pushing up inflation uncertainty through some monetary policy mechanism compared to a negative inflation shock of the same magnitude (Rizvi *et al.*, 2014).

The final measure of inflation uncertainty in this study is an extension of the one obtained from the GARCH model but asymmetric effects of negative and positive shocks are duly accounted for. The exponential GARCH (EGARCH) adequately models these effects. This measure allows for a straightforward assessment of how inflation uncertainty responds to inflation surprises/shocks. This class of ARCH/GARCH model (i.e. EGARCH) was developed and proposed by Nelson (1991) to solve the shortcomings of the GARCH model's failure to generate a time-varying variance for the variable that is responding to its mean (Wilson, 2006). The EGARCH model of inflation is given by:

$$\ln(¢_t^{2}) = µ + \sum_{i=1}^{p} ª_i \ln(¢_{t-i}^{2}) + \sum_{j=1}^{r} ¨_j \left(\left| \frac{£_{t-j}}{\sqrt{¢_{t-j}^{2}}} \right| \right) - E\left| \frac{£_{t-j}}{\sqrt{¢_{t-j}^{2}}} \right| + ¶ \left(\frac{£_{t-j}}{\sqrt{¢_{t-j}^{2}}} \right) \qquad (8)$$

where $(£_{t-j} / \sqrt{¢_{t-j}^{2}})$ is assumed to be *i.i.d.* with zero mean and constant variance and E denotes the expectation sign. The superiority of the EGARCH over the GARCH model is that the variance specification in equation (8) captures the asymmetric effects ($¶$) of both good and bad news (i.e. past shocks) on one period ahead conditional variance. If $¶ \neq 0$, then the impact of news (good or bad) is asymmetric but leverage effect is imminent if $¶ < 0$. According to Wilson (2006), if $¶ < 0$, then the conditional variance ($¢_t^2$) will increase more in response to negative inflation shocks than to positive ones. Conversely, if $¶ > 0$, then $¢_t^2$ will increase more to positive inflation shocks ($£_{t-j} > 0$) than to negative shocks ($£_{t-j} < 0$). A positive inflation shock will have the same effect on uncertainty similar to a negative shock of equal magnitude if $¶ = 0$. That is, there are no asymmetric effects if $¶ = 0$. Also, given the logarithmic form of the conditional variance, the presence of negative parameters will still make $¢_t^2$ positive thus removing imposed constraints on the GARCH parameters. Thus forecast of the conditional variance in the EGARCH model is non-negative.

In the main quantile regression estimation, we use the measure of inflation uncertainty obtained from the GARCH model and use the other two uncertainty measures (i.e. standard deviation of inflation and EGARCH conditional variance) to check for robustness of our estimates.

4.4 Data

Monthly consumer price index (2010=100) data spanning the period 1963:03 to 2014:11 is obtained from the International Financial Statistics (IFS) of the IMF and utilized to generate the inflation rate and associated inflation volatilities. We calculate our measure of annualized monthly inflation as $® = (\ln ®_t - \ln ®_{t-12}) * 100$.

4. Results and discussion

Table 1 shows descriptive statistics of the data used for the empirical analysis. Inflation averaged about 23% over the period under consideration with a maximum rate of 100%. The results also show the three different inflation uncertainty measures with their respective mean, standard deviation, minimum and maximum rates over the period. The correlation matrix in the lower panel of the table suggests significant positive relationship between inflation and all three uncertainty measures. Similarly, all inflation uncertainty measures are strongly and significantly linked to each other with the strongest correlation observed for uncertainty measured by GARCH and EGARCH (about 96%). Clearly, the conclusion from the correlation analysis is indicative of a likelihood of support for the hypotheses that inflation uncertainty drives inflation and vice versa. We attempt a validation of these tentative results in our discussion of the OLS and quantile regression analysis.

Table 1. Descriptive statistics and correlation

Variable	Mean	Std. Dev.	Min.	Max.
Inflation rate $(\circledR)$	23.20	19.98	-12.88	100.85
Inflation uncertainty $(\circledR^{unc}_{GARCH})$	14.62	25.17	1.03	199.21
Inflation uncertainty $(\circledR^{unc}_{EGARCH})$	13.21	17.93	0.41	124.24
Inflation uncertainty $(\circledR^{unc}_{STD})$	2.49	1.95	0.43	9.56
Correlation matrix				
	$\circledR$	$\circledR^{unc}_{GARCH}$	$\circledR^{unc}_{EGARCH}$	$\circledR^{unc}_{STD}$
$\circledR$	1			
$\circledR^{unc}_{GARCH}$	0.245***	1		
$\circledR^{unc}_{EGARCH}$	0.3925***	0.9552***	1	
$\circledR^{unc}_{STD}$	0.3896***	0.6019***	0.6909***	1

Note: *** indicates statistical significance at the 1% level.

Prior to performing an empirical assessment of the Cukierman-Meltzer and Friedman-Ball hypotheses, we evaluate the time series properties of the measures of inflation and inflation uncertainty. We apply both Augmented Dickey-Fuller (ADF) and DF-GLS (Elliot *et al.*, 1996) tests to ascertain the unit root properties of the series and the results are reported in Table 2. We find overwhelming evidence that all variables are level stationary (i.e., $I(0)$) and therefore pose no spurious implication on the empirical estimates.

Table 2. Unit root tests

	H_0: $I(1)$			
	ADF		DF-GLS	
Variable	Const.	Const. & trend	Const.	Const. & trend
®	4.663***	-4.742***	-4.143***	-4.385***
®^{unc}_{GARCH}	-3.664***	-4.209***	-3.490***	-3.545***
®^{unc}_{EGARCH}	-3.270**	-4.058***	-3.067***	-3.134**
®^{unc}_{STD}	-4.422***	-5.180***	-4.416***	-4.725***

Note: *** and ** denote rejection of null hypothesis at the 1% and 5% levels, respectively.

We now turn to our baseline results. Table 3 reports results of the main predictions in our paper when we use inflation uncertainty obtained from the GARCH analysis (i.e., ®^{unc}_{GARCH}). For the purposes of comparison, the mean results from OLS and the quantile estimates are both shown to test the Cukierman-Meltzer and Friedman-Ball hypotheses. The standard errors obtained for the OLS estimates are heteroskedasticity-robust while bootstrap standard errors based on 500 replications are used for estimating the quantile equations. Results for both hypotheses are shown in Table 3 for inflation uncertainty measures based on GARCH and EGARCH. We do not show results for inflation uncertainty case measured by standard deviation[1] of inflation but are discussed in the analysis.

The Cukierman-Meltzer hypothesis is first assessed in the top panel of Table 3. All quantile regression estimates have been categorized into low (10^{th} – 30^{th}), medium (40^{th} – 60^{th}) and high (70^{th} – 90^{th}) quantiles. Our results reveal a strong support for the hypothesis given by the significant and positive impact of inflation uncertainty on inflation (OLS results). The conditional mean estimate (OLS) shows that on average, a percentage increase in inflation uncertainty increases inflation by about 0.19%. The contemporaneous relationship between inflation uncertainty and inflation is further confirmed in the quantile regression case. The 9 estimated quantiles of inflation given inflation uncertainty show a positive relation between the two variables. However, not all estimates of inflation uncertainty at each quantile appear to significantly drive inflation rates. The coefficient of inflation uncertainty is significant between the 20^{th} - 50^{th} and 80^{th} – 90^{th} quantiles. We also observe that the estimates of price uncertainty

[1] Full results can be obtained from the authors.

increases quite sharply from 0.047 at the 40th quantile to 1.160 at the 90th quantile. Across all quantiles, we observe inflation uncertainty does not equally drive inflation in terms of magnitude of impact. The inflation uncertainty effect is weaker at the lower quantiles than at medium and higher quantiles except for the 40th quantile which is relatively lower than the 20th and 30th quantiles. We further carry out tests to ascertain equality of slope across quantiles. The results clearly rejects the null hypothesis that inflation uncertainty impact inflation equally across all quantiles. Another interesting result is that there is substantial difference in impact of inflation uncertainty for the conditional mean and conditional median (50th quantile) cases. The average impact of inflation uncertainty in much stronger than the median effect.

Similarly, we find support for the Friedman-Ball hypothesis (results in 2nd panel of Table 3). That inflation significantly drives inflation uncertainty in Ghana is not rejected in both the conditional mean and quantile cases. However, we find the impact to be significant across all quantiles and increasing in magnitude as we move toward higher quantiles. Thus similar to the Cukierman-Meltzer results, the impact is much larger at higher quantiles than at lower quantiles. Interestingly, the coefficient of inflation in both the conditional mean and median scenarios are quantitatively indistinguishable except that the medium impact is slightly stronger than the mean impact. The quantile slope equality hypothesis is again rejected.

Figure 1 illustrates graphically results of the quantile regression and OLS estimates with estimated confidence interval bands. As already discussed, the OLS graph shows a constant mean estimate of the variable while the quantile plot shows the quantile point estimates for ^{2} as we increase it by 0.1 from 0.10 to 0.90. The solid curve denotes the change in the coefficient estimates given movement from one quantile point to another along the entire distribution of the variable. The confidence interval band, shown by the shaded area around the solid curve, is constructed via bootstrap method with 500 replications. It is clear from the visual inspection that unlike the conditional mean estimate which is constant, quantile estimates vary considerably across the complete distribution of the series being modelled.

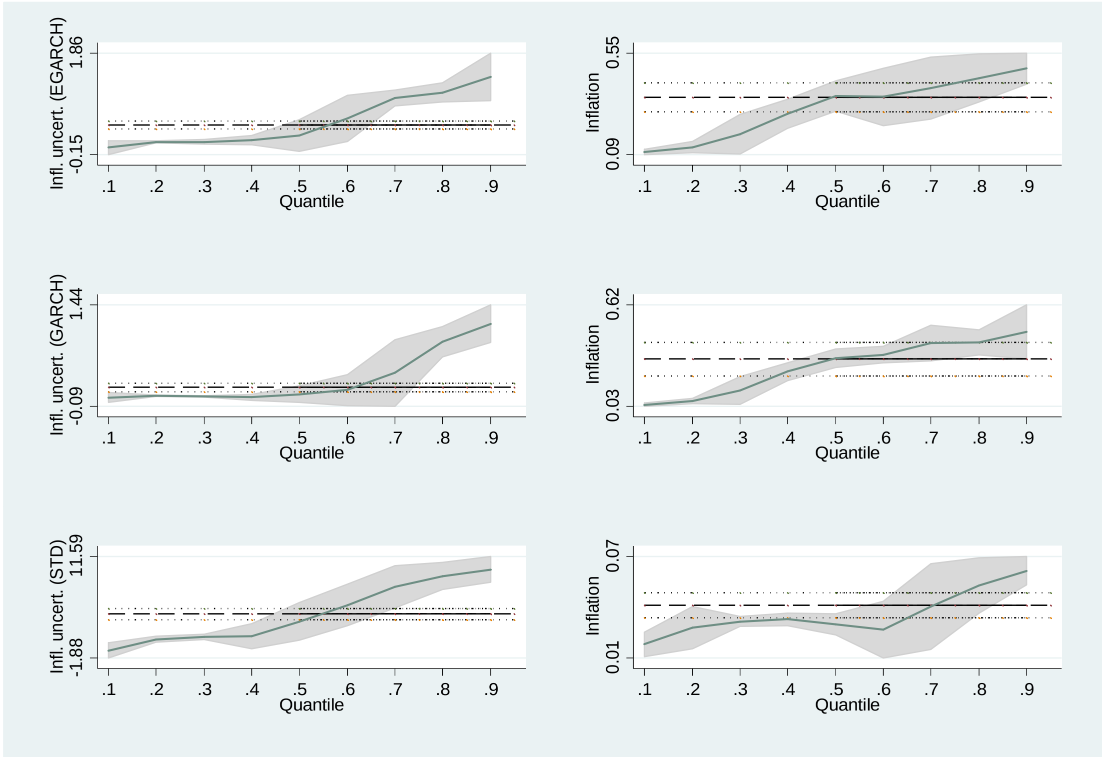

Figure 1. Quantile and OLS coefficients for quantiles ² ∈ (0,1)

4.1 Robustness checks

In this section, we perform sensitivity analysis to check for further validity and robustness of our estimates. First, re-estimate both OLS and quantile models but we use inflation uncertainty measures derived from EGARCH and standard deviation of the inflation series. Results from both measures used to test the twin hypotheses but only the case for EGARCH inflation uncertainty is reported in Table 3. Consistent with the baseline results, the conditional mean estimates again confirm a significant positive impact of inflation uncertainty on inflation with the reverse hypothesis also corroborated (3rd and 4th of Table 3) when inflation uncertainty is computed by a EGARCH(1, 1) model. Similar results are obtained when volatility in prices is represented by the standard deviation of inflation. With regard to the quantile estimates, a surprising yet interesting outcome is observable (Table 3). The Cukierman-Meltzer hypothesis is again corroborated at all quantiles except for the lower tail of the inflation uncertainty (from

Table 3. Quantile regression estimates

	Variable	Quantile									
			Low			Medium			High		
		OLS	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
GARCH	Dep. var= ®										
	®$^{unc}_{GARCH}$	0.194***	0.043	0.068***	0.058***	0.047*	0.094*	0.158	0.415	0.887***	1.160***
		(0.048)	(0.03)	(0.007)	(0.01)	(0.027)	(0.048)	(0.134)	(0.253)	(0.145)	(0.172)
	Intercept	20.358***	6.978***	9.097***	10.965***	13.692***	15.513***	18.998***	21.401***	25.456***	31.042***
		(0.779)	(0.969)	(0.321)	(0.405)	(0.459)	(0.729)	(1.15)	(1.841)	(1.065)	(1.256)
		Slope equality across quantiles F(8, 604) = 11.95 p-value=0.0000									
	Dep. var= ®$^{unc}_{GARCH}$										
	®	0.309***	0.041***	0.062***	0.125***	0.235***	0.314***	0.334***	0.404***	0.407***	0.466***
		(0.031)	(0.004)	(0.007)	(0.039)	(0.037)	(0.034)	(0.039)	(0.058)	(0.053)	(0.077)
	Intercept	7.46***	0.678***	0.631***	0.113	-0.828**	-0.911**	1.498	4.174***	11.305***	20.172***
		(1.272)	(0.05)	(0.097)	(0.47)	(0.401)	(0.524)	(1.082)	(1.305)	(2.049)	(3.023)
		Slope equality across quantiles F(8, 604) = 11.14 p-value=0.0000									
EGARCH	Dep. var= ®										
	®$^{unc}_{EGARCH}$	0.437***	-0.013	0.101***	0.101***	0.138***	0.23*	0.563**	0.977***	1.085***	1.392***
		(0.073)	(0.069)	(0.011)	(0.029)	(0.051)	(0.126)	(0.221)	(0.112)	(0.108)	(0.206)
	Intercept	17.424***	7.92***	8.97***	10.682***	12.976***	14.33***	16.299***	18.105***	23.317***	28.149***
		(0.819)	(0.777)	(0.263)	(0.394)	(0.497)	(0.711)	(1.259)	(1.05)	(0.938)	(1.096)
		Slope equality across quantiles F(8, 604) =17.57 p-value=0.0000									
	Dep. var= ®$^{unc}_{EGARCH}$										
	®	0.352***	0.102***	0.123***	0.183***	0.278***	0.36***	0.354***	0.396***	0.441***	0.485***
		(0.03)	(0.007)	(0.01)	(0.039)	(0.033)	(0.029)	(0.049)	(0.068)	(0.049)	(0.042)
	Intercept	5.037***	-0.437***	-0.28	-0.737	-1.479***	-1.812***	1.444	5.493***	10.779***	19.425***
		(0.929)	(0.113)	(0.161)	(0.496)	(0.372)	(0.5)	(1.724)	(1.437)	(1.948)	(2.012)
		Slope equality across quantiles F(8, 604) = 23.82 p-value=0.0000									

Note: ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively. Values in parenthesis are robust standard errors calculate based on bootstrap with 500 replications.

EGARCH) distribution where we find that volatility in prices drives down inflation albeit not significantly. Again, the results suggest that inflation uncertainty impact strongly on inflation at the upper tail of its (inflation uncertainty) distribution. In contrast, the Friedman-Ball hypothesis is overwhelmingly confirmed across all quantiles. Estimated coefficients at all quantiles are significant at the 1% level, with the median quantile having a stronger impact on inflation uncertainty than that of inflation uncertainty on inflation.

There is very little to choose between the results obtained from EGARCH as inflation uncertainty measure and the standard deviation of inflation. Table 3 clearly show robust results for both conditional mean and quantile coefficients. However, the reported negative effect of inflation uncertainty at the lower quantile (10^{th}) is statistically significant at the 5% level. The standard deviation of inflation quantitatively at the lower 10^{th} end of the uncertainty distribution has a stronger impact ($|-0.875|$) than the EGARCH measure of uncertainty ($|-0.013|$). These results suggest that there is some useful information in the inflation uncertainty distribution, at least in the lower tail, which can potentially drive down the level of inflation (a contradiction of the hypothesis). Monetary authorities could therefore exploit this information content in the formulation and implementation of price stability policies to drive down rising rates of inflation. This isolated result however confirms the Holland (1995) hypothesis. That is, at the 10^{th} (lowest) quantile, the standard deviation of inflation (i.e. high inflation uncertainty) causes low inflation. This result implies that the (monetary) policy authorities had exhibited stabilization behaviour as postulated by the Holland (1995) hypothesis by reducing growth in money supply in order to reduce inflation uncertainty and consequent adverse welfare effects (see Vioria, 2014). Figure 3 shows the same effects graphically as reported in Tables 3 by way of quantile plots. One can visually distinguish between the constant conditional mean effect and tractable quantile estimates along the inflation uncertainty and inflation distribution as a way of analysing the increasing trend of either variable on the other as formally hypothesized.

As a further check for robustness, we test the stated hypotheses using pairwise Granger-causality tests. The results[2] table are not reported here but main findings are discussed. Implementing Granger causality test at different lag lengths (4, 8 and 12) and using all three measures of inflation uncertainty show conclusive evidence that there is a bi-directional causality between inflation and its variability.

Overall, results from all the tests seem to overwhelmingly provide validation to the main results obtained from both conditional mean and quantile regression.

4.2 Policy discussion of results

Results of our empirical study could prove useful in complementing policy toolkits available to decision-makers in designing, implementing and/or adjusting monetary policy stance. The most crucial implication of the results holds that if the Friedman-Ball and/or Cukierman-Meltzer hypotheses are validated, then monetary authorities could (or should) consider an inflation targeting policy in order to reduce inflation uncertainty and its negative effect on inflation and economic growth in the medium-to-long term. Given Ghana's monetary policy stance has changed from a monetary to an inflating targeting policy framework since 2007, this study brings to the fore new evidence on this critical macroeconomic nexus in the literature and in practice.

The results from this paper show heterogeneous effect of either series on the other along the distribution of each outcome variable. Importantly, the effects are stronger and pronounced at upper quantiles of the distribution, evidence impossible to detect from a conditional mean estimate. Another implication of the results is that targeting inflation around the mean value of the distribution of the inflation series may be a poor policy choice since any deviation from the target could be costly for policy-makers, consumers and economy at large. This, our analysis indicates, could be solved if the entire distribution of the inflation/uncertainty dynamic is carefully examined to ascertain where along the distribution (lower, medium or upper) impact of

[2] Results are available on request.

the other is least or most severe so appropriate policy response(s) could be initiated to ensure price stability and sustained economic growth.

5. Concluding remarks

This paper presents a robust analysis of the nexus between inflation and inflation uncertainty in Ghana. We use the most complete and recent data on year-on-year monthly inflation rates spanning about 5 decades (1963:03 to 2014:11) and apply quantile regression techniques to test whether the hypotheses that inflation uncertainty increases inflation or the converse can be upheld in the case of Ghana. Quantile regression techniques provide vital information on inflation and inflation uncertainty along the lower, middle and upper tails of their respective distributions and the varying impacts on each other across all quantiles. The results show that generally inflation uncertainty raises inflation while the opposite is also confirmed for Ghana. This means that the Cukierman-Meltzer and Friedman-Ball hypotheses are valid on Ghanaian inflation data similar to findings by Barimah and Amuakwa-Mensah (2013), Sintim-Aboagye (2011), Sintim-Aboagye (2013) and Oteng-Abayie and Doe (2013). To the extent that either inflation or its variability has varying and significant impact across different quantiles raises important questions regarding inferences made on traditional conditional mean point estimates of these two variables. Since the impact of both inflation and its uncertainty on each other are not constant but vary across their respective distribution, then inferences made on conditional mean estimates must be treated with considerable caution.

Findings from the present study have important implication for monetary policy conduct in Ghana which merits consideration. The Bank of Ghana and other managers of the economy must augment their policy toolkits with detailed and careful analysis of inflation and associated variability dynamics via quantile regression analysis in order to have a complete picture of expected effects of policies. This would enable policymakers to not only understand the key drivers of Ghanaian inflation, but also the distributional impacts often concealed in many econometric techniques. Furthermore, the results would prove useful for policymakers, especially Ghana's Central Bank as it seeks to consolidate the relative macroeconomic gains made since implementation of its inflation targeting regime in 2007 and current and future inflation outlook which have assumed an upward trajectory in recent times. Upside risks have been heightened on the basis of high domestic interest rates, escalating fiscal deficits, ballooning public sector wage bill, fuel price hikes, recurrent energy crisis and negative business expectations. Thus efforts should be made taking into consideration all available information on relevant policy variables that drives down inflation uncertainty in Ghana in order to keep rates of inflation within reasonable growth-enhancing ranges. This would improve the general macroeconomic outlook and health of the economy as expectations and speculative activities are effectively managed.

Furthermore, monetary policy conduct by the Bank of Ghana should aim at firmly anchoring inflation expectations to reduce persistence in the medium-to-long-term. To achieve this, the Central Bank must further commit itself to greater transparency by improving its communications strategy and accountability to give the current monetary policy framework more credibility. To tame inflation within growth-enhancing limits, policy tightening through complementary mix of monetary and fiscal policies is recommended. In particular, prudent fiscal management through controlled public expenditure beyond an optimal threshold must be vigorously pursued. Macroeconomic policies aimed at stabilizing the exchange rate against rapid depreciation are also critical to achieving moderate inflation rates to boost growth.

In conclusion, we concede that our analysis could be extended in future studies to include other relevant macroeconomic variables such as real output growth, interest rate and exchange rate among others to also assess the direction and magnitude of their impacts within a quantile regression framework. Further, in concert with similar admission by Yeh *et al.*, (2011), future empirical work could be subjected to utilizing recent inferential methods in quantile regression analysis to include semi-parametric and non-parametric methods to avert likely misspecification of the imposed "structural" model.

References

Adu, G. and Marbuah, G. (2011). Determinants of Inflation in Ghana: An Empirical Investigation. *South African Journal of Economics* 79(3): 251-269.

Ball, L. (1992). Why does high inflation raise inflation uncertainty? *Journal of Monetary Economics* 29: 371-388.

Ball, L. and Ceccheti, S. G. (1990). Inflation and Uncertainty at Short and Long Horizons. *Brookings Papers in Economic Activity* 1: 215-254.

Barimah, A. and Amuakwa-Mensah, F. (2013). Does Inflation Uncertainty Decrease with Inflation? A GARCH Model of Inflation and Inflation Uncertainty. *West Africa Journal of Monetary and Economic Integration.* 12(2):32-61.

Caporale, G.M., L. Onorante, and P. Paesani, (2009), Inflation and Inflation Uncertainty in the Euro Area,.*CESifo Working Paper* No. 2720.

Cameron, A. C. and Trivedi, P. K. (2010). Microeconometrics Using Stata. Revised Edition. Stata Press, Texas, USA.

Chen, S-W., Shen, C-H. and Xie, Z. (2008). Evidence of a nonlinear relationship between inflation and inflation uncertainty: The case of the four little dragons. *Journal of Policy Modeling* 30(2), 327-343.

Çiçek, S. and Akar, C. (2013), The Asymmetry of Inflation Adjustment in Turkey. *Economic Modelling* 31, 104–118

Cukierman, A. and Meltzer, A. H. (1986). A Theory of Ambiguity, Credibility, and Inflation under Discretion and Asymmetric Information. *Econometrica* 54(5): 1099-1128.

Elliott, G., Rothenberg, T. J. and Stock, J. H. (1996). Efficient Tests for an Autoregressive Unit Root. *Econometrica* 64, 813-836.

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* 50(4): 987-1007.

Fang, W. S., Lee, C. S. and Miller, S.M. (2010), What can we learn about inflation targeting? Evidence from time-varying treatment. *SSRN Working Paper Series*.

Fountas S., (2001), The Relationship between Inflation and Inflation Uncertainty in the UK; 1885-1998. *Economics Letters*, 74, p. 77-83.

Fountas, S., Karanasos. M., (2007), Inflation, Output Growth, and Nominal and Real Uncertainty: Empirical Evidence for the G7. *Journal of International Money and Finance*, 26 (2007), p. 229-250.

Friedman, M. (1977). Nobel Lecture: Inflation and Unemployment. *Journal of Political Economy* 85(3): 451-472.

Grier K. B., Grier, R., (2006). On the Real Effects of Inflation on Inflation Uncertainty in Mexico. *Journal of Development Economics*, 80, p. 478-500.

Hegerty, S. W. (2012), Does High Inflation Lead to Increased Inflation Uncertainty? Evidence from Nine African Countries. *African Economic and Business Review* Vol. 10, No. 2.

Holland, A. S., (1995), Inflation and Uncertainty: Test for Temporal Ordering. *Journal of Money, Credit and Banking*, 27, p.827-837

Koenker, R. (2005). *Quantile Regression*. Cambridge University Press, New York, USA.

Koenker, R. and Hallock, K. F. (2001). Quantile Regression. *Journal of Economic Perspectives* 15(4): 143-156.

Koenker, R. and Bassett, G. (1978). Quantile Regressions. *Econometrica* 46(1): 33-50.

Korap, L. (2010). Threshold GARCH modeling of the inflation & inflation uncertainty relationship: historical evidence from the Turkish economy. *MPRA Paper* 31765, University Library of Munich, Germany.

Marbuah, G. (2011). On the Inflation-Growth Nexus: Testing for Optimal Inflation for Ghana. *Journal of Monetary and Economic Integration* 11(2): 54-82.

Mladenoviæ, Z. (2009), Relationship between Inflation and Inflation Uncertainty: The Case of Serbia. *Yugoslav Journal of Operations Research*, Vol. 19 (2009), Number 1, 171-183.

Neanidis, C. K. and Savva, S. C., (2011), Nominal Uncertainty and Inflation: The role of European Union Membership. *Economic Letters,* 112, p. 26-30.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: a new approach. *Econometrica* 59, 347-370.

Okun, A. M. (1971). The Mirage of Steady Inflation. *Brookings Papers in Economic Activity* 2: 485-498.

Oteng-Abayie, E. F. and Doe, S. K. (2013). Inflation and Inflation Uncertainty in Ghana. *Journal of Business Management and Economics* 4(12): 259-266.

Özdemir, A. Z. and M. Fisunoğlu, (2008), On the Inflation-Uncertainty Hypothesis in Jordan, Philippines and Turkey: A Long Memory Approach. *International Review of Economics & Finance*, 17, 1, p.1-12

Payne, E. J., (2008), Inflation and Inflation Uncertainty: Evidence from the Caribbean Region. *Journal of Economic Studies*, 35, 6, p.501- 511.

Pourgerami, A. and Maskus, K., (1987), The Effects of Inflation on the Predictability of Price Changes in Latin America: Some Estimates and Policy Implications. *World Development*, 15, 1, p. 287-290.

Pourshahabi, F., Dahmardeh, N., and Khani, Z. A. M., (2010) Asymmetry Effect of Inflation on Inflation Uncertainty in Iran: Using from EGARCH Model, 1959-2009. *American Journal of Applied Sciences*, 7, 535-539.

Rizvi, S. K. Abbas, Naqvi, B., Bordes ,C. and Mirza, N. (2014). Inflation volatility: An Asian perspective, *Economic Research-Ekonomska Istraživanja*, 27(1), 280-303.

Salmanpour, A. and Bahloli, P. (2011), Inflation, Inflation Uncertainty and Factors Affecting Inflation in Iran. *World Applied Sciences Journal* 14 (8): 1225-1239.

Samimi, A. J., Mohamadreza, A. and Ghader (2012), Inflation and Inflation Uncertainty: Evidence from MENA. *Universal Journal of Management and Social Sciences*. Vol. 2, No.1 p57-62

Sintim-Aboagye, H. (2011). Effect of Economic Recovery and Adjustment Policies on the Friedman-Ball Hypothesis and the Cointegration of Inflation and the Uncertainty of Inflation in Africa. *Oxford Journal: An International Journal of Business and Economics* 6(1): 54-60

Sintim-Aboagye, H. (2013). IMF and World Bank Economic Programs on Inflation: Relevance of NEPAD. *Review of Applied Economics* 9(1-2): 61-81.

Thorton J., (2007), The Relationship between Inflation and Inflation Uncertainty in Emerging Market Economies. *Southern Economic Journal*, 73, 4, 858-870.

Thorton J., (2008), Inflation and Inflation Uncertainty in Argentina, 1810-2005. *Economic Letters*, 98, p.247-252.

Tillmann, P. and Wolters, M. H. (2014), The changing dynamics of US persistence: a quantile regression approach. *Kiel Working Paper* 1951, IfW Publikationen von Forscherinnen und Forschern des IfW

Tsong. C. C., and Lee, C. F. (2011). Asymmetric inflation dynamics: Evidence from quantile regression analysis. *Journal of Macroeconomics* 33, 668-680.

Wilson, B. K. (2006). The links between inflation, inflation uncertainty and output growth: New time series evidence from Japan. *Journal of Macroeconomics* 28: 609-620.

Yeh, C-C., Wang, K-M. and Suen, Y-B. (2011). A Quantile framework for Analysing the links between Inflation Uncertainty and Inflation Dynamics across Countries. *Applied Economics* 43(20): 2593-2602.