“Quantile analyzing the dynamic linkage between inflation uncertainty and inflation”

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Abstract

In contrast to conventional conditional mean approaches, this study uses quantile regression techniques to present some new statistical evidence on the links between inflation uncertainty and the level of inflation with cross sectional data in 90 countries for the period of 1961-2002. The results that suggest positive inflation shocks have stronger impact on inflation uncertainty vary across the quantiles. Furthermore, popular time series models that are evaluated for their ability to reproduce measures of uncertainty indicate similar results for relationships between inflation and inflation uncertainty.

Keywords: inflation, inflation uncertainty, quantile regression, GARCH, EGARCH, CGARCH.
JEL Classification: C14, C21, O11, O15.

Introduction

Both price stability and inflation share a wide consensus among macroeconomists and policymakers as critical factors for the economy as a whole. It is rather surprising, therefore, that a study about the relationships between these two variables has yet to emerge. While early studies by Friedman's (1977) Nobel Lecture suggested an exploitable linkage between inflation uncertainty and the level of inflation, the large swings experienced in the United States over the period of 1960-88 belied this finding. Ball and Cecchetti (1990), Evans (1991) and Ball (1992) also provide evidence of such an effect. The most basic test of inflation-inflation uncertainty consists of estimating a conditional mean approach where the explanatory variable is the average inflation rate and the dependent variable is the standard deviation of inflation or a moving standard deviation of the variable under consideration[1].

Economists frequently study the relationship between inflation and inflation uncertainty because of its importance for policy analysis. Theoretically, Friedman (1977) first outlined an informal argument regarding the positive correlation between the level of inflation and inflation uncertainty, with higher inflation leading to greater uncertainty and lower output growth. These inferences, in turn, are easily recognized when we consider how uncertainty about inflation is likely to affect policy decision making. With these differences in mind, we shall use the cross sectional data with the quantile regression model in subsequent sections to reexamine the relationship between variance of inflation and inflation rate.

The motivation to use quantile regressions on the inflation-inflation uncertainty is twofold. First, the quantile regression estimator is robust to outlying observations on the dependent variable. This is an important perspective given that the unconditional inflation uncertainty distribution is characterized by right tails, as can be seen, for instance, in Baillie et al. (1996). Second, the quantile regression estimator gives, potentially, one solution to each quantile. Therefore, we may assess how policy variables affect countries according to their position on the inflation uncertainty distribution. Using quantile method is an interesting way of capturing the countries' heterogeneity. In our case, the patterns of inflation and inflation uncertainty imply that the coefficient on the inflation uncertainty increases with the quantiles, suggesting that the impact effect is stronger, in some sense, for countries in the upper quantiles. In other words, we assert that since the quantile estimates change so dramatically across the distribution, it is unlikely that mere data differences could be solely responsible.

In contrast to previous work, Ball and Cecchetti (1990) and Evans (1991) both discover the linkage between inflation rates and inflation uncertainty under mean approach. They propose a model that puts Evans (1991) approach within the time-varying parameter and ARCH specification good setting. From the linkage of inflation-inflation uncertainty that includes time variation in the structure of inflation, the paper next covers a case of Brunner's (1993), Markov switching model with inflationary dynamics as inflation regimes, also proposed in Telatar and Telatar (2003). This model with temporal ordering added is used in Holland (1995). The paper then turns to cross-country models that are compared to Davis and Kanago (1997). Then the paper sets out models with GARCH family approaches for estimating the relationship between inflation and inflation uncertainty, proposed in Grier and Perry (1996, 1998), Fountas (2001), Giordani and Sőderlind (2003), Apergis (2004), Elder (2004),

[1] These earlier studies used the standard deviation of the inflation rate, proposed in Okun (1971), Gordon (1971), Louge and Willet (1976), Jaffe and Kleiman (1977), Gale (1981), Hafer and Heyne-Hafer (1981), Ram (1985), Chowdhury (1991), Edmonds and So (1993), Emery (1993), David and Kanago (1996), Hess and Morries (1996) which facilitate this analysis.

Kontonikas (2004), Berument and Dincer (2005), Daal et al. (2005) which facilitate this analysis. Most existing evidence regarding the validity of the Friedman hypothesis is still far from incontrovertible. Finally, Cohrad and Karanasos (2005) put forth research that implies parametric models of long memory in both the conditional mean and the conditional variance of inflation to investigate the relationship between inflation and inflation uncertainty. Then, less robust evidence is found regarding the direction of the impact of an increased nominal inflation on inflation uncertainty.

Yet, there are also empirical findings against the Friedman hypothesis. For instance, Davis and Kanago (1998) argue that the Friedman hypothesis works better for a cross section of countries at a point in time than for the evolution of inflation over time within countries. It turns out that the results do not support the existence of the Friedman hypothesis. Furthermore, Hwang (2001) uses time series data with various ARFIMA-GARCH type models, but does not find evidence in favor of Friedman's view. In addition, Berument et al.'s (2005) evidence from using a time-varying parameter model with a GARCH specification, has flatly rejected that notion, contending that inflation uncertainty does not necessarily signify the level of inflation rates.

However, many studies on the relationship between inflation and its volatility which used GARCH type models are mainly focused on estimating the conditional mean function while the mean effects obtained via the conditional mean regression offer intriguing summary statistics for measuring the impact of covariates, they fail to characterize the full distributional impact. In contrast, this article applies the quantile regression introduced by Koenker and Bassett (1978), to examine the validity of the Friedman hypothesis across different quantiles of the unconditional inflation uncertainty distribution. As is well known, quantile regression has become an increasingly important tool in estimating quantile-specific effects that describe the impact of variables not only on the center but also on the tails of the outcome distribution. Fang et al. (2007) provide the application of the quantile regression method and threshold inflation rate to examine two-way causality between inflation and alternative measures for the variability of inflation. They interpret the lack of possible time series estimate with inflation uncertainty.

The contribution of this article is to estimate the unconditional inflation-inflation uncertainty for broadly constituted samples using quantile regressions. The estimated quantile regression process on the higher inflation uncertainty exhibits a steeper upward trend at approximately the 75th and 95th quantiles. This finding suggests that there is evidence of unconditional inflation-inflation uncertainty for countries in the upper tail of the conditional distribution of inflation uncertainty but weak effects among countries in the lower tail. This result is in contrast with previous estimates obtained with conditional mean estimation methods such as generalized autoregressive conditional heteroskedasticity (GARCH) for individual countries. For instance, Ungar and Zilberfarb (1993) and Hwang (2001) show that a high rate of inflation does not necessarily imply a high variance of inflation. The quantile specification model not only can reduce inconsistent bias for unit time-series regression, but also remove country's heteroskedasticity with cross sectional studies.

This article is divided as follows. Section 1 provides a brief review of the quantile regression estimation method and its properties. Section 2 introduces the estimates of the regression quantiles for the unconditional inflation uncertainty equation. Section 3 includes the robustness check of the inflation uncertainty measured via the difference GARCH approaches for quantile regression. Section 4 describes the data sources and summarizes the empirical results. Finally, the last section concludes.

1. A brief introduction to quantile regression

Much of applied econometrics may be viewed as an elaboration of the linear regression model and associated estimation methods of ordinary least squares (OLS) and least absolute deviation (LAD). It is well known that the former method estimates this by minimizing the sum of the squared errors and results in an approximation to the mean function of the conditional distribution of the regressand. The later method minimizes the sum of absolute errors and fits medians to a linear function of covariates. A useful feature of the quantile regression is distinct from them as not binding that represents a central tendency of a distribution. We could go further and compute several different regression curves corresponding to the various percentage points of the distributions and thus get a more complete picture of the set. As far as the entire conditional distribution is concerned, it is not satisfactory to characterize only the mean (or median) behavior. In other words, quantile regression is robust to the presence of outliers.

Now we briefly discuss the quantile regression estimation procedure and some properties of the quantile regression estimator. The quantile regression, first proposed by Koenker and Bassett (1978), has the appealing feature that it can estimate a family of conditional quantile functions that provide us with a more complete picture of covariate effects. Given that any real-valued random variable X may be characterized by its distribution function as

$$F(x) = Pr(X \le x) \quad (1)$$

the θ^{th} quantile, for $0 < \theta < 1$, is defined as

$$Q(\theta) = \inf\{x : F(X) \ge \theta)\}, \quad (2)$$

where X is a random variable with the distribution function given by equation (1). The definition of quantile simply says that an observation in the θ^{th} percentile is greater than θ% of the observations and smaller than $(1-\theta)$% of the observations. We let $(y_i, x_i), i = 1,2,3\ldots n$, be a sample from some population, where y_i is a real outcome variable of interest and x_i is a vector of regressors including policy variables. The general quantile regression, described in Bunchinsky (1998), takes the linear form:

$$y_i = x_i\beta_\theta + \varepsilon_\theta \quad (3)$$

for $i = 1,2,\cdots,n$, where β is a ($k \times 1$) vector of coefficients, x_i is the column vector that is the transposition of the i^{th} row of the $X_{n\times k}$ matrix of explanatory variables, y_i is the i^{th} observation of the dependent variable and ε_θ is the unknown error term. The θ^{th} conditional quantile of y given x can be rewritten as

$$Qunant_\theta = (y_i \mid x_i) = x_i^{'}\beta_\theta\,. \quad (4)$$

Its estimate is given by $x_i'\beta_\theta$. As θ increases continuously, the conditional distribution of y given x is traced out. Then, it is assumed that the conditional quantile of y_i, conditional on x_i, satisfies $Qunant_\theta = (y_i \mid x_i) = x_i'\beta_\theta$, for several different values of θ , $\theta \in (0,1)$, so that $Qunant_\theta = (y_i \mid x_i) = 0$. It is in this way that quantile regression allows for parameter heterogeneity across different types of regressors. Thus, the quantile regression estimator can be found as the solution to the following minimization problem:

$$\min_{\beta\in\Re^k}\left[\sum_{i\in\{i:y_i\}\ge x_i\beta}\theta\left|y_i - x_i^{'}\beta\right| + \sum_{i\in\{i:y_i\}\ge x_i\beta}(1-\theta)\left|y_i - x_i^{'}\beta\right|\right]. \quad (5)$$

The quantile function is a weighted sum of the absolute value of the residuals. Where the weights are symmetric for the median regression case in $\theta = 1/2$, the minimization problem above reduces to $min_{\beta\in\Re^K}\sum_{i=1}^{n}\left|y_i - x_i'\beta\right|$, and asymmetric otherwise. By varying the value of parameter θ from 0 to 1, we can generate the entire conditional distribution of y given x. In practice, we consider the partial derivative of the conditional quantile of y with respect to one of the regressors, coefficients of policy variable, can be interpreted as the marginal change in the dependent variable due to a marginal change in the policy variable. Note that since we have on β for each θ, the quantile regression approach allows us to identify the effects of the covariates on the regressand at different points on the distribution. In particular, as shown in Koenker and Hallock (2001), an attractive property of the quantile regression estimator is its robustness to incorporating the presence of outlying observations on the dependent variable. Interested readers are referred to Koenker (2004, 2005) for more details.

2. The unconditional inflation uncertainty equation

Assuming that the 'θ^{th}' quantile of the conditional distribution of dependent variable is linear in the explanatory variable, following Koenker and Bassett (1978), the unconditional quantile regression model can be applied to the following two equations to examine the relationship between inflation and inflation uncertainty.

$$u_i = \alpha_\theta + \beta_\theta\pi_i + \varepsilon_{\theta i}\,. \quad (6)$$

The terms π and u denote inflation and inflation uncertainty in equation (6), respectively. α_θ and β_θ are the unknown parameters to be estimated for different values of θ, and ε_θ is the usual disturbance. Signs on the inflation rate are predicted to be positive. By varying the value of θ from 0 to 1, we can trace the entire distribution of dependent variable conditional on the independent variable. Just as we can define the least squares estimators for obtaining the conditional mean function as the solution to the problem of minimizing a sum of squared residuals, the quantile estimators for β_θ can be obtained by minimizing the following asymmetric linear penalty function as equation (5). For reasons discussed above, the quantile regression has the appealing feature that it can estimate a family of unconditional quantile functions that offer us a more complete picture of covariate effects.

3. Robustness and heteroskedasticity: measures of inflation uncertainty

Following the literature, several robustness checks were undertaken as far as the specification is concerned, and a focus was given to the extent of heteroskedasticity bias likely to arise from a possible country specific of inflation and inflation uncertainty. In terms of the robustness of the inflation uncertainty variable, several authors experiment with different econometric specifications. Below we present three sets of time-series regression for measures of inflation uncertainty.

First, we follow Gultekin (1983) to use contemporaneous inflation rates as proxies for expected inflation. The realized values are used under the assumption that expectations are rational. Second, we rely on a pure ARIMA model to generate expected inflation and unexpected inflation. Inflation forecasts from ARIMA regressions are used as indicators of expected inflation while the forecast errors are used as the measure of unexpected inflation π_{it}^{u}. The model can be described as

$$\pi_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \pi_{t-i} + \sum_{j=1}^{q} \phi_j v_{t-j} \,, \tag{7}$$

where v_t is a white noise.

Third, in order to allow for conditional heteroskedasticity, we assume that $v_t \big| \Omega_{t-1} = h_t^{\frac{1}{2}} \eta_t$ and $\eta_t \sim NID(0,1)$. Particularly, we consider three alternative specifications of the conditional variance h_t for each country. The first one is the GARCH(1,1) process set out by Bollerslev (1986) which can be specified as

$$h_t = a_0 + a_1 h_{t-1} + b_1 v_{t-1}^2 \,. \tag{8}$$

By taking into account the asymmetric effects of negative and positive shocks, our second specification for the conditional variance is the exponential GARCH (EGARCH) process proposed by Nelson (1991). The specification can be written as

$$\ln(h_t) = a_0 + a_1 \ln(h_{t-1}) + b_1 \left| \frac{v_{1-t}}{\sqrt{h_{t-1}}} \right| + c_1 \frac{v_{t-1}}{\sqrt{h_{t-1}}} \,. \tag{9}$$

Our third and last model for the conditional variance is an extension of the basic GARCH model. Engle and Lee (1999) represent the GARCH(1,1) model as characterized by reversion to a constant mean $\bar{\mu}$, i.e.,

$$h_t = \bar{\mu} + a_1 (h_{t-1} - \bar{\mu}) + b_1 (v_{t-1}^2 - \bar{\mu}) \,. \tag{10}$$

In contrast, their component GARCH (CGARCH) process allows reversion to a time varying mean m_t, modeled as

$$\begin{aligned} h_t - m_t &= \bar{\mu} + a_1 (h_{t-1} - \bar{\mu}) + b_1 (v_{t-1}^2 - \bar{\mu}), \\ m_t &= \mu + \rho (m_{t-1} - \mu) + \delta (v_{t-1}^2 - h_{t-1}). \end{aligned} \tag{11}$$

By estimating equation (7) along with respective equations (8), (9) and (11), we can obtain expected and unexpected components of inflation. Moreover, we follow conventional applications such as Asteriou and Price (2005) and Byrne and Davis (2005a, 2005b) to proxy inflation uncertainty by the logarithm of the fitted (conditional) volatility values from equations (8), (9) and (11), respectively. Correspondingly, the inflation uncertainty measures h_{it} are denoted as $GAR(\pi)$, $\mathrm{EG}(\pi)$ and $CG(\pi)$, respectively. After running those time-series relation for each country in our data, a bit of perspective on previous results is helpful.

4. Data description and empirical results

4.1. Data sources. The data set used in this paper was collected primarily from the "Global Development Finance & World Development Indicators, 2005" which contains inflation rates with cross sectional data in 90 countries for the time period from 1961 to 2002. The list of countries can be found in Appendix A. The inflation series is obtained by taking the logarithm of the growth rate of the CPI index. The popular method for measuring inflation uncertainty is the standard deviation of the inflation rate. Existing research evidence of a positive relation between inflation and inflation uncertainty is most frequently found in cross-country studies that regress some measure of variability or uncertainty for each country on their average inflation rate. However, some time-series regressions for individual countries have not reached a unanimous conclusion. Those time-series studies that derive inflation uncertainty from a GARCH model conclude that higher inflation causes greater uncertainty. Non-surprisingly, several generalizations follow from the GARCH sets of inflation uncertainty-inflation regression with insignificant coefficients on inflation. (For evidence, see Engle (1983), Bollerslev (1986), Edmonds and So (1993)). To assess the robustness of the results, we experiment with inflation uncertainty following GARCH, component-GARCH (CGARCH) and exponential GARCH (EGARCH), respectively. Table 1 shows the summary statistics and correlation matrix of these variables. Obviously such correlation is simply a measure of linear association, and tells us nothing about any non-linear effect. Again, there does suggest a strong, positive inflation effect on the inflation uncertainty.

Table 1. Summary statistics and correlation matrix

Panel A: Summary statistics						
Variables	Mean	Median	Min.	Max.	Std.	Obs.
Inflation rates (π)	11.9661	8.1544	2.7424	60.2831	11.6299	90
Std(π)	14.0080	7.4220	1.8010	179.4942	24.8063	90
GAR(π)	8.0360	4.7638	0.9931	70.7782	11.1431	90
EG(π)	6.7613	4.6115	0.9602	48.8221	7.8085	90
CG(π)	6.5948	4.3372	1.0481	56.5782	7.5055	90
Panel B: Sample correlation of inflation and inflation uncertainty						
Variables	π	Std(π)	GAR(π)	EG(π)	CG(π)	
Inflation rates (π)	1.0000					
Std(π)	0.8577	1.0000				
GAR(π)	0.7301	0.6399	1.0000			
EG(π)	0.6900	0.5874	0.9650	1.0000		
CG(π)	0.6959	0.5838	0.9483	0.9393	1.0000	

Note: The dataset is taken from the "Global Development Finance & World Development, 2005" and is a cross-sectional dataset consisting of 90 countries observed from 1961 to 2002. The list of countries can be found in Appendix A. Inflation (π) equals the annual rate calculated as the percentage change in the logarithm of consumer price index. Std(π) is the cross-sectional average individual standard deviation of inflation; GAR(π), EG(π) and CG(π) identify the cross-sectional average individual under GARCH, EGARCH and CGARCH inference, respectively.

4.2. The results of parametric quantile models. Panel A of Table 2 provides the estimation results of equation (6) from the parametric mean and quantile regressions. In the simplest form, the conditional mean results in column (1) show that the estimate of ' π ' is 1.8294, as significant at the 1% level, and has the expected sign, thus, providing a preliminary support of the Friedman's hypothesis.

Table 2. Main regression results of coefficients across quantiles

Panel A: Estimates of Friedman-Ball regression model, $u_i = \alpha_\theta + \beta_\theta \pi_i + \varepsilon_{\theta i}$						
		Quantile				
	OLS	0.05th	0.25th	0.50th	0.75th	0.95th
α_θ	-7.8830 (3.4700)	-0.3083 (0.6181)	-0.7554*** (0.2255)	-2.0342*** (0.3150)	-5.5183*** (1.2493)	-7.0585*** (1.4940)
β_θ	1.8294*** (0.3892)	0.6170*** (0.0198)	0.8305*** (0.0136)	1.1313*** (0.0191)	2.0429*** (0.0776)	3.0946*** (0.0569)
Panel B: F-statistics testing for slope equality across quantiles						
Quantile						
0.25th		2.16 (0.15)				
0.50th		6.38*** (0.01)	4.20** (0.04)			
0.75th		7.22*** (0.01)	5.98** (0.02)	4.18** (0.04)		
0.95th		28.40*** (0.00)	25.74*** (0.00)	20.49*** (0.00)	4.12** (0.05)	

Note: ' π ' represents inflation rates and ' u ' is inflation uncertainty. Numbers in parentheses are standard errors in Panel A. Numbers in parentheses are p-values in Panel B. ***, **, and * denote significance at 1%, 5% and 10% level, respectively.

In contrast, five quantile estimates for the most basic specification are also obtained for θ = 0.05, 0.25, 0.5, 0.75 and 0.95 and shown in columns (2) to (6). For those coefficients that are significant at the 1% level in a given equation, the magnitude of the coefficients varies widely across the quantiles. The quantile process for inflation exhibits a linear increasing trend. For countries in the bottom 5% of the conditional inflation uncertainty distribution, the estimated coefficient on inflation is 0.6170, it increases to 1.1313 for countries in the conditional median, and increases again to 3.0946 in the top 5% of the distribution. These results suggest that the effect of inflation has a stronger impact on countries in the upper tail of the inflation uncertainty distribution. These findings are suggestive of the potential information gains associated with the estimation of the entire conditional inflation uncertainty distribution, as opposed to only the conditional mean. Moreover, a comparison of the estimates of the conditional median function with OLS estimates of the conditional mean function reveals that the traditional estimation techniques are affected by the tails of the data distribution.

Panel B of Table 2 shows the results of the Wald test for equality of slope coefficients across the quantiles for the independent variables. These test results show that the slope coefficients indeed vary across the quantiles. The slopes are significantly different from each other between the 50th, 75th and 95th percentile for the 5th quantile and the 25th quantile and between the 75th and 95th quantile for the median quantile. These test results confirm the argument that the relationship between the inflation and inflation uncertainty along with the inflation affect the inflation uncertainty differently across the quantiles.

Figure 1 shows the linear pattern with the parametric quantile regression of equation (6). Superimposed on the plot are five estimated quantile regression lines corresponding to the quantiles {0.05, 0.25, 0.5, 0.75, 0.95} and OLS linear regression line. The median $\theta = 0.5$ fit is indicated by the dotted line. The 95th quantile still has a steeper pattern and 5th quantile has a smooth pattern as compared with other quantiles. The plot clearly reveals the rising tendency of the dispersion of inflation uncertainty to increase along with its level as the inflation rate increases. In this case, our results also support the Friedman hypothesis that inflation increases the inflation uncertainty across the different quantiles of regression function. The quantile process function of $\hat{\beta}(\theta)$, plot in Figure 2 is the estimated quantiles of inflation uncertainty distribution. The plot discovers the linear increasing trend varies across the quantiles. The dotted bands represent confidence intervals which are significant. Interestingly, its linearity suggests that positive inflationary shocks are stronger on inflation uncertainty, in some sense, for countries in the upper tail.

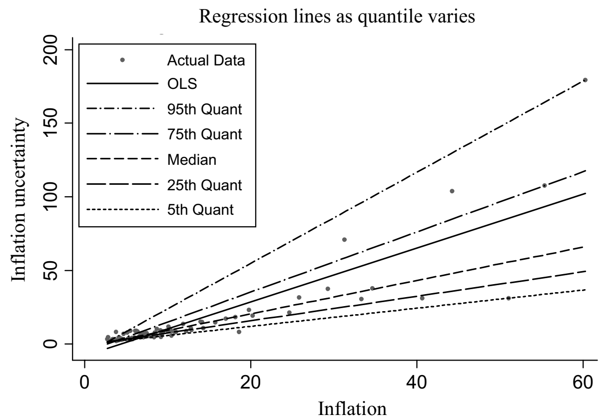

Fig. 1. Effect of an increase in inflation under quantiles

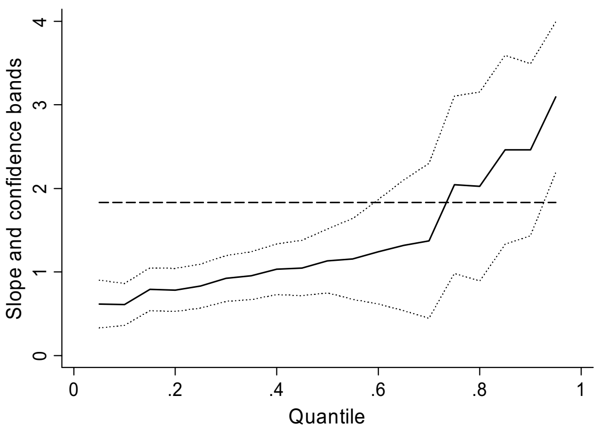

Fig. 2. The slope of the estimated linear regression function (6) plotted as a function of θ

4.3. Robustness checks. In this section the focus is on the overall model specification. All of the results are reported in Table 3 from the case when data observations are restructured from the sample countries. In terms of the robustness of the inflation uncertainty, we experiment with different GARCH-type sets of uncertainty variables included in the quantile econometric specification. There exist statistically significant relationships between inflation and the inflation uncertainty. For example, Panel A of Table 3 provides the coefficients on the inflation from equation (6). When the dependent variable is computed by GARCH(1,1), there are also significant relations. Similarly, a positive sign on inflation and increasing tendency implies a linear relationship. Panels B and C in Table 3 clearly show that the positive effect of inflation on inflation uncertainty is great at top tails of inflation uncertainty – in particular at levels above around 95%.

Table 3. Robustness check

Quantile regression model: $u_i = \alpha_\theta + \beta_\theta \pi_i + \varepsilon_{\theta i}$						
		Quantile				
	OLS	0.05th	0.25th	0.50th	0.75th	0.95th
Panel A: The inflation uncertainty (u) as measured by GARCH						
α_θ	-0.3348 (1.7034)	1.0311*** (0.2061)	-0.8644*** (0.1719)	0.0039 (0.4996)	0.2592 (0.5832)	-1.9005 (2.7902)
β_θ	0.6995*** (0.2004)	0.0624*** (0.0075)	0.5389*** (0.0109)	0.5659*** (0.0296)	0.7672*** (0.0341)	1.6433*** (0.1630)
Panel B: The inflation uncertainty (u) as measured by EGARCH						
α_θ	1.2180 (1.1673)	0.9474*** (0.1644)	0.1509 (0.3527)	0.6409 (0.4622)	0.4453 (0.4102)	-0.3309 (4.3128)
β_θ	0.4633*** (0.1383)	0.0609*** (0.0060)	0.3560*** (0.0227)	0.4737*** (0.0280)	0.6689*** (0.0244)	1.0651*** (0.2035)
Panel C: The inflation uncertainty (u) as measured by CGARCH						
α_θ	1.2211 (1.2496)	1.0826*** (0.1369)	0.1890 (0.3073)	0.4411 (0.3809)	0.2092 (0.6924)	0.0166 (0.6816)
β_θ	0.4491*** (0.1447)	0.0511*** (0.0050)	0.3365*** (0.0199)	0 .4604*** (0.0231)	0.6708*** (0.0419)	1.2789*** (0.0220)

Note: ' π ' represents inflation rates and ' u ' is inflation uncertainty. Numbers in parentheses are standard errors. ***, **, and * denote significance at 1%, 5% and 10% level, respectively.

Concluding remarks

This paper presents a general linkage effect between inflation and inflation uncertainty using quantile regression methods. In this procedure, quantile-specific parameters may capture the country's heterogeneity and characterize the full distribution of inflation uncertainty. The estimates we gathered via the new set of specifications suggest that inflation causes inflation uncertainty in favor of Friedman's hypothesis. There is a significant and positive relation across countries between average inflation and inflation uncertainty. Besides, one particularly interesting result we find is the increasing linearity pattern of the regression quantile process on the inflation coefficient. Each slope coefficient can be interpreted as a different impact of the inflation uncertainty to a change in an inflation variable, according to a country's position on the inflation uncertainty distribution. This is an interesting way of capturing parameter heterogeneity. This finding shows that the effect of inflation on the inflation uncertainty is stronger for countries in the upper quantiles than for those in the lower quantiles. In other words, quantile regression model can exhibit a significant evidence of the inflation rate on the rate invoking the inflation uncertainty incurring high costs for countries in the top quantiles. Finally, our results can be subject to further investigation, and extended in several ways. Application of recent inferential methods in quantile regression, such as semi-parametric and non-parametric to avoid possible model misspecifications, is a natural extension of our framework. Moreover, the latest version of the IMF data set contains a number of important macroeconomic variables that we didn't discuss here. Investigation on how these policy variables relate to inflation and inflation uncertainty as a sensitivity analysis can also be an interesting extension

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Appendix for reviewers

Appendix A: List of the 90 countries in the sample

Country name	Inflation	Country name	Inflation	Country name	Inflation
Algeria	11.0341	Guatemala	9.1513	Norway	5.5585
Australia	5.7179	Haiti	10.3962	Pakistan	7.8082
Austria	3.8512	Honduras	9.2021	Panama	2.7424
Bahamas	5.1361	Hungary	12.2611	Papua New Guinea	8.3663
Bahrain	4.7079	Iceland	20.2447	Paraguay	12.8903
Barbados	7.3829	India	60.2831	Philippines	10.4294
Belgium	4.1604	Iran, Islamic Rep.	14.3116	Poland	44.2284
Burkina Faso	5.1787	Ireland	7.1115	Portugal	10.8349
Burundi	10.0395	Italy	7.5990	Saudi Arabia	3.7935
Cameroon	7.4547	Jamaica	15.7290	Senegal	6.3265
Canada	4.5814	Japan	4.1892	Seychelles	7.0073
Chile	55.3769	Jordan	7.0731	Sierra Leone	29.2635
Colombia	18.6128	Kenya	10.3779	Singapore	2.8345
Costa Rica	13.9883	Korea, Rep.	9.3528	South Africa	9.2119
Cote d'Ivoire	6.7798	Kuwait	4.4191	Spain	8.4528
Cyprus	4.3376	Libya	6.8086	Sri Lanka	8.6515
Denmark	5.7856	Luxembourg	3.8988	Sudan	34.6573
Dominican Rep.	11.8725	Madagascar	12.7852	Suriname	31.2630
Ecuador	24.6394	Malaysia	3.3435	Swaziland	10.4946
Egypt	9.3489	Malta	3.4176	Sweden	5.6437
El Salvador	9.4517	Mauritius	8.4874	Switzerland	3.3065
Ethiopia	6.0981	Mexico	25.8222	Syrian Arab Rep.	10.1106
Fiji	7.1186	Morocco	5.3619	Togo	6.3803
Finland	6.0335	Myanmar	14.1315	Trinidad and Tobago	8.0249
France	5.2756	Nepal	8.2838	Turkey	40.6237
Gabon	6.2339	Netherlands	4.1240	United Kingdom	6.6286
Gambia	8.7182	Netherlands Antilles	4.1353	United States	4.4309
Germany	3.0783	New Zealand	7.0155	Uruguay	51.0247
Ghana	33.3301	Niger	5.5282	Venezuela	19.7736
Greece	10.8851	Nigeria	18.1377	Zimbabwe	16.9954

Appendix B: Wald test for equality of coefficients across quantiles

	GAR(π)				EG(π)				CG(π)			
Quantile	5th Q	25th Q	50th Q	75th Q	5th Q	25th Q	50th Q	75th Q	5th Q	25th Q	50th Q	75th Q
25th Q	7.25*** (0.01)				5.23** (0.02)				5.27** (0.02)			
50th Q	8.30*** (0.01)	0.04 (0.83)			8.81*** (0.00)	1.49 (0.23)			9.11*** (0.00)	1.95 (0.17)		
75th Q	7.95*** (0.01)	1.11 (0.30)	1.29 (0.26)		10.85*** (0.00)	4.33** (0.04)	2.72* (0.10)		10.76*** (0.00)	4.64** (0.03)	2.88* (0.09)	
95th Q	14.02*** (0.00)	7.57*** (0.01)	7.92*** (0.01)	5.53** (0.02)	6.64*** (0.01)	3.59* (0.06)	2.66 (0.11)	1.33 (0.25)	15.63*** (0.00)	10.75*** (0.00)	8.86*** (0.00)	5.69** (0.02)

Note: The numbers present F-statistic of equality of the slope coefficients at $u_i = \alpha_\theta + \beta_\theta \pi_i + \varepsilon_{\theta i}$ across quantiles. The associated p-values are reported in parentheses. ***, **, and * denote significance at 1%, 5% and 10% level, respectively.