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Inflation Uncertainty and Output Growth - Evidence from the Asia-Pacific Countries Based on the Multiscale Bayesian Quantile Inference*

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Abstract

This paper investigates how inflation uncertainty affects real GDP growth in five Asia-Pacific countries – Australia, New Zealand, Japan, South Korea and Indonesia, whereby these countries adopted inflation targeting (IT) strategy at some point in time. We use several elaborate methodologies – wavelet technique, GARCH with innovative distributions and the Bayesian quantile regression. We determine that inflation uncertainty negatively (positively) affects real GDP growth in periods of economic contraction (prosperity) in all the countries. In addition, the results indicate that this effect is notably stronger in the period after IT than in the period before IT, which particularly applies for Australia, New Zealand, Japan and Korea. As for Indonesia, the impact of inflation uncertainty to real GDP growth is very similar in both subsamples, because expectations about high inflation in Indonesia are well-rooted. The conclusion indicates that if country pursue reliable anti-inflationary policy, output growth can be affected relatively significantly by an excess inflation uncertainty. However, this is not the case in the systems, which are not based on a prudent and well-established anti-inflationary policy, such as Indonesian.

1. Introduction

It is well established in both theoretical and empirical fronts that the price level and its uncertainty (volatility) have far-reaching effect on the overall economic welfare and economic system. Friedman (1977) laid a foundation for this conviction, emphasizing that rising inflation instigates a strong pressure from monetary authorities to counter it, which consequently creates uncertainty among general public about the course of future inflation. Later studies further tried to explain conduits through which inflation uncertainty spills over to real aggregates. For instance, Beaudry et al. (2001) asserted that managers are unable to detect profitable investment opportunities during periods of high inflation uncertainty, because they can hardly extract information about the relative prices of goods. Wilson (2006) and Grecu et al. (2020) argued that economic system becomes less efficient in economic

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activity coordination in rising inflation uncertainty environment, which eventually causes a decline in output growth. Along this line, Bloom (200 9) contended that inflation uncertainty shocks generate a rapid drop and rebound in output and employment, since companies temporarily pause their investment and hiring, which eventually slows down economic growth. Caglayan et al. (2016) added that external funds become prohibitively expensive in periods of high uncertainty, which forces managers to delay or cancel investment projects, impeding in this way output growth.

However, in spite of the fact that many studies investigated the influences of inflation and inflation uncertainty on the real economy, Chang and He (2010) contended that these empirical studies offer mostly contradictory conclusions. Fountas and Karanasos (2007) explained the reasons why this is the case. They stated that results are highly sensitive to several factors such as the measure of inflation uncertainty, the chosen econometric methodology, the countries examined, and the sample period. Therefore, it is reasonable to believe that the empirical literature on this subject is divided, which requires a further investigation in this area.

According to the aforementioned, this paper tries to add to the literature by thoroughly investigating the nexus between inflation uncertainty and real economic growth in the five Asia-Pacific countries – Australia, New Zealand, Japan, South Korea and Indonesia. In particular, this research underlines several important aspects. First, the selected countries from the region are intentionally chosen because all these economies have adopted inflation targeting strategy at some point in time. More specifically, Australia conducts IT policy since June 1993, New Zealand since January 1990, Japan since January 2013, South Korea since April 1998 and Indonesia since July 2005[1]. In addition, we choose these particular countries because three of them are developed and two are emerging markets, and this selection is good for the comparison purposes. Also, a relevant argument for the choice of these countries is the fact that four of them apply forward-looking strategy of IT, whereas only Indonesia considers backward-looking IT policy, and it is useful to see how (whether) inflation uncertainty affect output growth in these two distinctively different systems.

Table 1 Empirical Values of Real GDP Growth and Inflation in Full Sample and Two Subsamples

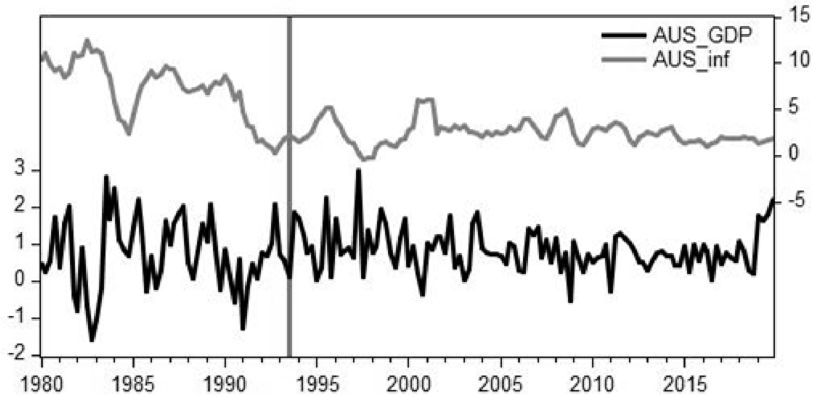
	Whole sample		***Before IT***		***After IT***	
	Real GDP	***Inflation***	***Real GDP***	***Inflation***	***Real GDP***	***Inflation***
Australia	0.791	4.046	0.715	7.135	0.830	2.473
New Zealand	0.691	2.542	0.000	7.490	0.746	2.130
Japan	0.494	0.986	0.526	0.976	0.350	0.810
South Korea	1.513	4.751	1.990	7.430	1.133	2.437
Indonesia	1.353	9.386	1.113	12.503	1.605	6.107

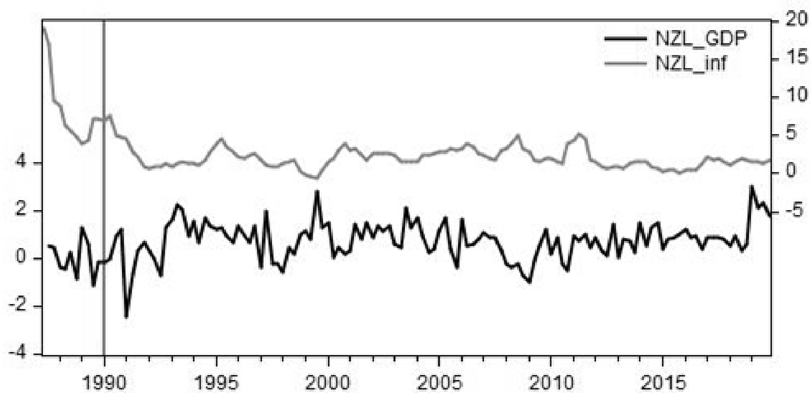
Source: Authors' calculation.

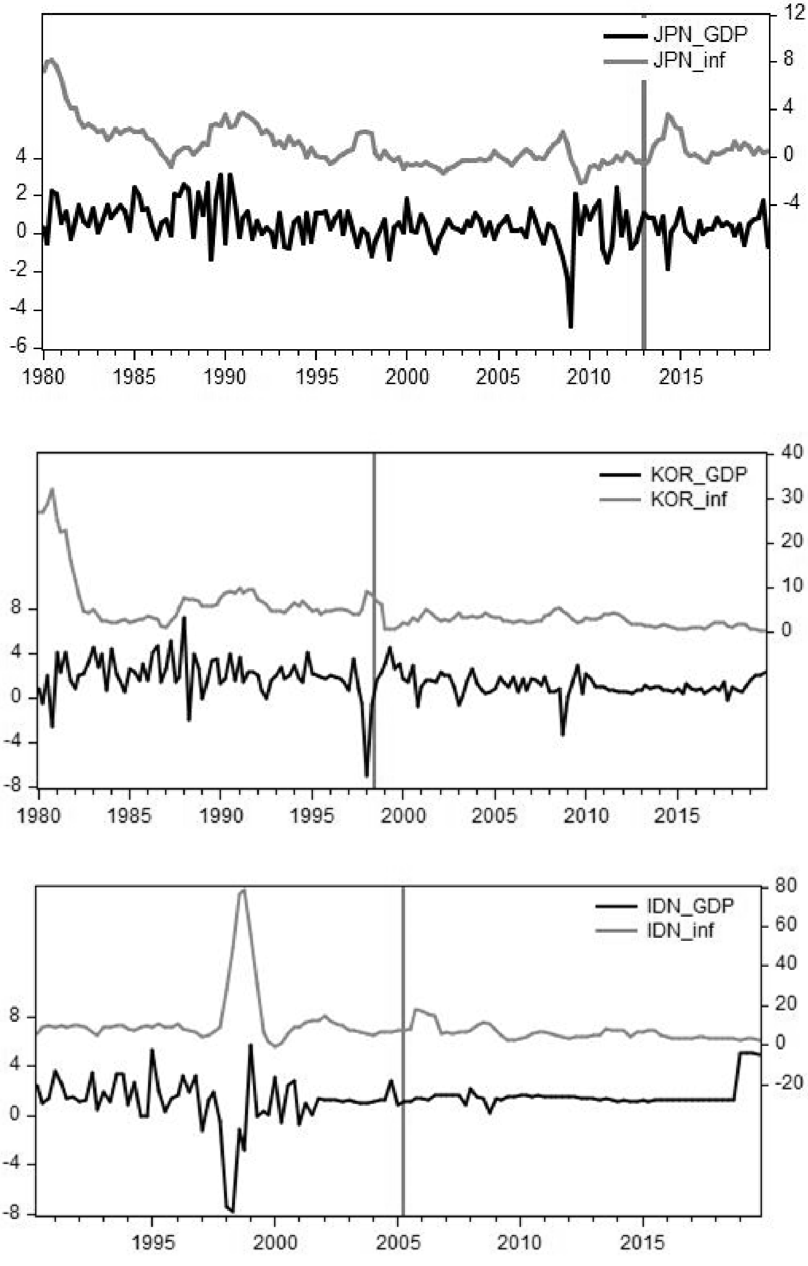
[1] Thailand and Philippines also belong to the Asia-Pacific region, and they adopted IT in May 2000 and January 2002, respectively. However, availability of the empirical data for these two countries are too short for our type of investigation, so they are omitted from the sample. All other countries from the region did not implement IT strategy as a monetary policy, and as such were not considered in this paper.

IT is a practical monetary strategy, which enhances credibility of monetary authorities and raises accountability and transparency of a central bank (see Pincheira and Medel, 2015). Thus, in addition to the full sample estimation, we also split full sample of every country into two subsamples – before and after IT introduction. In this way, we can determine is there any difference in the inflation uncertainty-GDP interaction when different sub-samples are observed, i.e. before IT and after IT. This procedure is justifiable because the level of annual inflation significantly differs between the subperiods for all the countries examined, according to Table 1. In other words, in the period after IT introduction, inflation rates are considerably lower comparing to the period when this strategy was not conducted. Therefore, it could be assumed *a priory* that inflation uncertainty has less effect on real GDP under an IT regime, but this contention needs to be verified empirically. Figure 1 depicts graphically empirical dynamics of real GDP and inflation in the selected countries, whereby it indicates that inflation rates are obviously lower in the period after IT.

Figure 1 Empirical Dynamics of Real GDP Growth and Inflation for the Selected Countries







Notes: Three letters abbreviations – AUS (Australia), NZL (New Zealand), JPN (Japan), IDN (Indonesia) and KOR (South Korea). Vertical line indicates the period when IT strategy was implemented.

Source: Authors' calculation.

Second, we want to analyse the transmission effect between the variables not only from the temporal domain, but from the frequency point of view as well. In other words, we try to assess how inflation uncertainty impacts real output growth in different time-horizons, i.e. in the short-term, midterm and long-term. Conlon and Cotter (2012) explained why relatively limited number of papers analysed frequency domain. They asserted that the main issue is a sample reduction problem, which arises when researchers try to match the frequency of data with the different time-horizons. In order to circumvent this issue, this study uses the wavelet signal-decomposing series, which preserve information contained in the empirical series, but at the same time, they allow researcher to observe different time-horizons. In recent years, many researchers used the wavelet technique to study various economic phenomena in different time-horizons (see e.g. Madaleno and Pinho, 2012; Dajčman, 2012; Barunik and Vacha, 2013; Lee and Lee, 2016; Barunik et al., 2016; Živkov et al., 2018; Tsai and Chang, 2018; Živkov et al., 2019a).

Third, we endeavour to gauge inflation uncertainty as accurate as possible. This is done after we transform the empirical series into the wavelet-decomposed signals. In that effort, we employ several GARCH specifications, which help us to find an optimal measure for inflation uncertainty proxy. The used GARCH models assumes different traditional and innovative distribution functions – normal, Student-t, generalized asymmetric Student-t (GAT) and generalized extreme value (GEV). In addition, following Caglayan et al. (2016), we learn that taking into account the possible structural break effect in the variance is equally important in the process of inflation uncertainty measurement. Thus, in addition to the estimation of several GARCH models with the alternative distribution functions, we also utilize Markov switching GARCH (MS-GARCH) model with normal distribution, which can efficiently recognize structural breaks endogenously.

In the last stage of our three-step procedure, we imbed wavelet-based series in the Bayesian quantile regression (QR) framework, which is capable of providing an insight about the transmission effect from inflation uncertainty to real GDP growth in different market conditions – downturn (lower quantiles), normality (intermediate quantiles), and upturn (upper quantiles). Also, this methodology can recognize the underlying nonlinearities in the data, which prevents biased conclusions. Technically speaking, Bayesian QR uses MCMC (Markov Chain Monte Carlo) algorithm in the estimation process, which provides an exact inference about the quantile parameters. In other words, all estimated Bayesian quantile parameters are highly statistically significant, even in low data environment, such as ours[2]. Yet another important fact is that the Bayesian QR methodology decreases the length of credible intervals and increases the accurateness of quantile estimates, comparing to the traditional quantile regression OLS approach of Koenker and Bassett (1978).

This paper differentiates from the existing literature along several dimensions. Based on our knowledge, this study is the first one that stipulates the level of transmission effect from inflation uncertainty to real GDP in different time-horizons, using wavelet methodology. In addition, an important characteristic of this study is that we put an emphasis on the accurateness of the results. This is achieved by the

[2] A total number of quarterly observations for Australia, Japan and South Korea is 160. For New Zaeland and Indonesia it is 130 and 119, respectively.

precise measurement of inflation uncertainty *via* an optimal GARCH model, while the Bayesian QR method ensures the robustness of the quantile parameters, which significantly contributes to reliability of the results.

Besides introduction, the rest of the paper is structured as follows. Second section provides brief literature review. Third section explains used methodologies. Forth section is reserved for dataset. Fifth section contains the results, while the last section offers concluding remarks.

2. Brief Literature Review

The relationship between inflation uncertainty and output growth is one of the most debated subjects in macroeconomy and numerous authors contributed on this topic, but with rather heterogeneous results. For instance, Fountas and Karanasos (2007) studied G7, using univariate GARCH models in the period 1957-2000. They found mixed evidence regarding the effect of inflation uncertainty on output growth and concluded that inflation uncertainty is not necessarily detrimental to economic growth. Wilson (2006) used a bivariate EGARCH-M model of Japanese inflation and growth to examine the links between inflation, inflation uncertainty and growth. He reported strong evidence that increased inflation uncertainty raises average inflation and lowers average growth in Japan. The paper of Wu et al. (2003) examined the effects of inflation uncertainties on real GDP in the U.S. and they concluded that different sources of inflation uncertainty have different impacts on real GDP. Their results suggested that inflation uncertainty has negative impacts on the real GDP. Hartmann and Roestel (2013) considered VARX-MGARCH-M models for 34 developed and emerging economies and the time period of 1990–2010. Their cross-country robust evidence indicated that both inflation and inflation uncertainty significantly reduce output growth, whereby economies with low inflation are particularly at risk to incur output losses from increasing inflation.

Fountas (2010) researched the relationship between inflation uncertainty, inflation and growth in industrial countries, using annual historical data. He strongly asserted that inflation uncertainty is not detrimental to output growth. Jiranyakul and Opiela (2011) investigated the impact of inflation uncertainty on output growth in Thailand, employing a bivariate constant conditional correlation generalized autoregressive conditional heteroskedastic specification. They revealed that increased inflation uncertainty decreases output in Thailand. The paper of Chowdhury et al. (2018) utilized a bivariate regime switching model in order to study the regime-dependent effects of inflation uncertainty and output growth uncertainty on inflation and output growth in the United Kingdom and the United States. They concluded that inflation uncertainty has negative effect on output growth mainly during the period of economic contraction in both countries. They underlined that higher real uncertainty significantly reduces output growth only in their low output growth regimes. Bhar and Mallik (2010) used a multivariate EGARCH-M model in order to research the effects of inflation uncertainty and growth uncertainty on inflation and output growth in the United States. Their results showed that inflation uncertainty has a positive and significant effect on the level of inflation and a negative and significant effect on the output growth.

3. Methodologies

3.1 Wavelet Approach

First step in our three-step procedure involves transformation of empirical time-series into wavelet signals, in order to observe how inflation uncertainty impacts GDP growth in different time horizons. This question is important for monetary policy-makers who wants to focus on high, medium and low frequency variations of a price index. For this task, we use wavelet technique, which is capable of decomposing time-series into their time-frequency components without wasting of valuable information (Njegić et al., 2017; Živkov et al., 2019c). Nikkinen et al. (2011) explained that wavelet methodology allows an appropriate trade-off between resolution in the time and frequency domains, which traditional Fourier analysis cannot do. Wavelet theory is familiar with the two key wavelet functions: the father wavelet (ϕ) and the mother wavelet (ψ). Father wavelets augment the representation of the smooth or low frequency parts of a signal with an integral equal to 1, whereas the mother wavelets can describe the details of high frequency components with an integral equal to 0. In other words, father wavelet portrays the long-term trend over the scale of the time-series, whereas the mother wavelet delineates fluctuations in the trend. Father wavelet $\phi_{J,k}(t)$ and mother wavelet $\psi_{j,k}(t)$ functions can be calculated as in equation (1):

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(\frac{t-2^J k}{2^J}\right), \qquad \psi_{j,k}(t) = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right) \tag{1}$$

We utilize particular type of wavelet transformation – the maximum overlap discrete wavelet transformation (MODWT) algorithm[3], which is based on a highly redundant non-orthogonal transformation. In that sense, a signal-decomposing procedure in MODWT is given in the following way:

$$S_J(t) = \sum_k S_{J,k}\phi_{J,k}(t) \tag{2}$$

$$D_j(t) = \sum_k D_{j,k}\psi_{j,k}(t) \qquad j = 1,2,\dots,J \tag{3}$$

where symbols $S_J(t)$ and $D_j(t)$ denote the fluctuation and scaling coefficients, respectively, at the j-th level wavelet that reconstructs the signal in terms of a specific frequency (trending and fluctuation components). Accordingly, an empirical time series y(t) can be expressed in terms of those signals as:

$$y(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t). \tag{4}$$

3.2 Creating Inflation Uncertainty Proxy

One of the important questions of this paper is the precise measurement of inflation uncertainties, with aim to improve the assessment of these estimates. According to Chen et al. (2008), a major weakness of a simple GARCH-normal type model is that it assumes a specific functional form before any estimations are made,

[3] Wavelet transformation was done via 'waveslim' package in 'R' software.

which can produce biased coefficient estimates and standard errors. In that regard, we take into account GARCH specification with two traditional and two non-traditional distribution functions – normal, Student-t, generalized asymmetric Student-t (GAT) distributions and generalized extreme value (GEV)[4]. The primary motive to use two alternative, non-traditional distributions (GAT and GEV) lies in the fact that they have theoretical advantages over the common normal distribution in modelling the tail distribution of inflation uncertainty, and as such, can potentially improve its assessment (see e.g. Kresta and Tichy, 2012; Živkov et al., 2019b). The existence of fat-tailed properties of inflation can easily be seen in Figure 1, hence the usage of GEV and GAT distributions is justifiable. In addition, we also consider possible presence of structural breaks in the variance by employing the Markov switching GARCH model with normal distribution[5]. In order to avoid biased parameter estimates, which can be caused by autocorrelation, we use AR(1) specification in the mean for all the selected inflation series. The mean equation and the single-regime GARCH process are given as in equations (5) and (6):

$$\pi_t = a_0 + a_1\pi_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim i.i.d.(0,1) \tag{5}$$

$$h_t = \omega_0 + \omega_1\varepsilon_{t-1}^2 + \omega_2 h_{t-1} \tag{6}$$

where π is the inflation rate computed as first difference of logarithm of consumer price index (CPI). h_t is the conditional variance with the conditions $\omega_0 \geq 0, \omega_1 \geq 0$ and $\omega_2 \geq 0$. The error term (ε_t) follows the $i.i.d.$ process, and the determination of the accurate distribution specification is in our focus.

Therefore, in addition to conventional distribution functions – normal $\varepsilon \sim N(0, h_t)$ and Student-t $\varepsilon \sim St(0, h_t, \upsilon)$, we also consider two heavy tailed distributions – GAT and GEV. In the following, we introduce a novel generalized asymmetric Student-t (GAT) distribution of Zhu and Galbraith (2010). According to these authors, GAT distribution uses one skewness parameter and two tail parameters, which provides the potential to better recognize the tail phenomena. GAT distribution is expressed in the following manner:

$$f_{gat}(y; \alpha, \upsilon_1, \upsilon_2, \mu, \sigma) = \begin{cases} \frac{1}{\sigma}\left[1 + \frac{1}{\upsilon_1}\left(\frac{y-\mu}{2\alpha\sigma K(\upsilon_1)}\right)^2\right]^{-(\upsilon_1+1)/2} & , y \leq \mu \\ \frac{1}{\sigma}\left[1 + \frac{1}{\upsilon_2}\left(\frac{y-\mu}{2(1-\alpha)\sigma K(\upsilon_2)}\right)^2\right]^{-(\upsilon_2+1)/2} & , y > \mu \end{cases} \tag{7}$$

where μ is the location parameter, while σ is the scale parameter. α is the skewness parameter with the condition $\alpha \in (0,1)$, whereas υ_1 and υ_2 are the left and right tails, respectively, conditioned by $\upsilon_1 > 0$ and $\upsilon_2 > 0$. $K(\upsilon) = \frac{\Gamma((\upsilon+1)/2)}{\sqrt{a}\Gamma(\upsilon/2)}$ and $\Gamma(\cdot)$ is the Gamma function.

[4] Estimation of GARCH-normal, GARCH-gat and GARCH-gev models was done via 'GEVStableGarch' package in 'R' software.
[5] Estimation of MS-GARCH model was done via 'MSGARCH' package in 'R' software.

Second unconventional heavy tail distribution is GEV distribution, which is suitable to capture extreme tail risk in the probability distribution. McNeil and Frey (2000) proposed the use of the Generalized Pareto Distribution (GPD), which is also known as the peak-over-threshold (POT) approach, to analyse the joint behaviour of the variables in the lower and upper tails. The POT approach extracts values from a sample of $i.i.d.$ observations X_t $(t = 1,2,\ldots,n)$ with a distribution function $F(x) = \Pr(X_i \leq x)$ by taking the exceedances above a certain threshold value u. The conditional distribution function F_u of the exceedances can be defined as:

$$F_u(y) = P(X - u \leq y | X > u) = \frac{F(y+u) - F(u)}{1 - F(u)} = \frac{F(x) - F(u)}{1 - F(u)} \quad \text{for} \quad y = (x - u) > 0 \tag{8}$$

Aloui and Jammazi (2015) asserted that the conditional distribution function F_u may be approximated by the GPD, $F_u(y) \approx GPD_{\xi,\sigma}(y), u \to \infty$, where $GPD_{\xi,\sigma}(y)$ can be written as:

$$GPD_{\xi,\sigma}(y) = \begin{cases} \left(1 + \frac{\xi}{\sigma} y\right)^{-\frac{1}{\xi}} & if \quad \xi \neq 0 \\ 1 - exp^{-\frac{1}{\sigma}} & if \quad \xi = 0 \end{cases} \tag{9}$$

where $\sigma > 0, y = x - u \geq 0$ if $\xi \geq 0$ and $0 \leq y - (\sigma/\xi)$ if $\xi < 0$. σ, ξ and u are the scale, the shape and the location parameters, respectively. The parameters of the GPD are estimated using the maximum-likelihood (ML) method.

In the last stage of a conditional variance measurement, we follow Frommel (2010) and employ Markov switching GARCH model of Gray (1996), which can recognize possible structural breaks in the variance. Conditional variance in the MS-GARCH model follows a GARCH(1,1) process as in equation (6), but this time we assume two possible regimes of the state variable (S_t) – low volatility and high volatility states. Therefore, the MS-GARCH model specification is as follows:

$$h_t = \omega_{1_{St}} + \omega_{2_{St}} \varepsilon_{t-1}^2 + \omega_{3_{St}} h_{t-1} \tag{10}$$

where $\omega_{1_{St}}$ is state dependent constant, whereas parameters $\omega_{2_{St}}$ and $\omega_{3_{St}}$ gauge an ARCH and GARCH effect, respectively, under particular regime S_t.

According to Marcucci (2005), Gray (1996) used information observable at time $t - 2$ to integrate out the unobserved regimes as in equation (10):

$$h_{t-1} = E_{t-2}\left(h_{t-1}^{(j)}\right) = p_{1,t-1}\left[\left(\mu_{t-1}^{(1)}\right)^2 + h_{t-1}^{(1)}\right] + \left(1 - p_{1,t-1}\right)\left[\left(\mu_{t-1}^{(2)}\right)^2 + h_{t-1}^{(2)}\right] -$$

$$\left[p_{1,t-1}\mu_{t-1}^{(1)} + \left(1 - p_{1,t-1}\right)\left(\mu_{t-1}^{(2)}\right)\right]^2 \tag{11}$$

where $j = 1,2$ and $\mu_t^{(j)}$ is conditional mean or location parameter.

3.3 Bayesian Quantile Regression

The last stage of our three-fold procedure involves insertion of optimal wavelet-based conditional volatilities and GDP time-series in the Bayesian quantile regression framework[6]. In its basis, QR approach extends the mean regression model to conditional quantiles of the response variable. In other words, this methodology gives a more elaborate view of the interlink between the dependent variable and the covariates, because it estimates how a set of covariates affect the different parts of the distribution of regressand. QR methodology has been found appealing by many researchers from various theoretical disciplines (see e.g. Dybczak and Galuščák, 2013; Maestri, 2013; and Vilerts, 2018). Due to the fact that inflation uncertainty is a generated regressor, we have to mention a caveat of Pagan (1984), in order to emphasize the correctness of our approach. He asserted that three issues can emerge from this situation: 1) consistency of estimation, 2) efficiency of estimation and 3) valid inference. According to this author, when only unlagged predictions appear as regressors, which is the case in equation (12), the two-step regression estimator satisfies three aforementioned conditions.

We start the explanation of the Bayesian QR methodology with the standard linear model as in equation (12):

$$y_i = \mu(x_i) + \varepsilon_i \tag{12}$$

where y_i denotes wavelet-based real GDP growth time-series, while x_i is corresponding wavelet-based inflation conditional volatility. Benoit and van den Poel (2017) explained that the regression coefficient in the case of all quantiles can be found by solving equation (13):

$$\hat{\beta}(\tau) = \operatorname{argmin} \textstyle\sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta); \quad \beta \in \Re \tag{13}$$

where $\tau \in (0,1)$ is any quantile of interest, while $\rho_\tau(z) = z(\tau - I(z < 0))$ and $I(\cdot)$ stands for the indicator function. The quantile $\hat{\beta}(\tau)$ is called the τ^{th} regression quantile. When $\tau = 0.5$, it corresponds to median regression. In the Bayesian procedure, QR parameters are estimated with the usage of the MCMC algorithm. An important characteristic of this process is the assessment of exact estimates of the quantile parameters $\hat{\beta}(\tau)$. According to Kruschke and Liddell (2018), Bayesian estimation process provides an explicit distribution of credibilities, which is called the posterior distribution across the parameter values. This type of distribution can be used to determine which parameter values are most credible, that is, what range of parameter values covers the most credible values. In particular, the posterior distribution can be directly interpreted, in a sense that the most credible parameter values can be read off. In the Bayesian estimation process, there is no need for p values and p value-based confidence intervals, because measures of uncertainty are based directly on posterior credible intervals.

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[6] Bayesian quantile parameters were calculated via 'bayesQR' package in 'R' software.

4. Dataset

This paper uses quarterly data of consumer price index (CPI) and real GDP growth rate of five Asia-Pacific countries – Australia, New Zealand, Japan, South Korea and Indonesia. Quarterly CPI indices are transformed into inflation rates ($r_{i,t}$), according to the expression: $r_{i,t} = 100 \times ln(CPI_{i,t}/CIP_{i,t-1})$. All the data are collected from OECD statistics. For Australia, Japan and South Korea, the sample ranges from 1980:Q1-2019:Q4. Due to data unavailability, for New Zealand and Indonesia, the sample is little bit shorter, and it starts from 1987:Q3 for New Zealand and 1990:Q2 for Indonesia. The end date for these two countries is also 2019:Q4.

Table 2 Descriptive Statistics of the Wavelet-Based GDP Growth Time-Series

		Mean	***St. dev.***	***Skewness***	***Kurtosis***	***JB***
	Australia	0.000	0.439	0.264	3.533	3.8
	New Zealand	0.000	0.446	-0.049	4.360	10.1
D1	*Japan*	0.000	0.475	-0.109	5.763	51.2
	Indonesia	0.000	0.960	-0.628	8.484	211.0
	South Korea	0.000	0.887	0.523	7.080	88.0
	Australia	0.000	0.373	-0.077	3.487	1.7
	New Zealand	0.000	0.368	-0.066	3.605	2.1
D2	*Japan*	0.000	0.475	-0.367	4.649	21.3
	Indonesia	0.000	0.661	-0.787	8.291	203.2
	South Korea	0.000	0.833	-0.650	10.190	264.7
	Australia	0.000	0.323	-0.119	5.434	39.9
	New Zealand	0.000	0.338	0.269	3.725	4.4
D3	*Japan*	0.000	0.381	-0.042	6.321	73.6
	Indonesia	0.000	0.615	-0.282	6.975	107.5
	South Korea	0.000	0.733	-0.921	9.483	225.3

Notes: JB stands for Jarque-Bera test of normality.

Source: Authors' calculation.

One of the goals of this paper is to assess how inflation uncertainty affects real GDP growth in different time-horizons. In that matter, we perform the wavelet transformation on the empirical time-series, where we observe 3 wavelet scales, which match different time-horizons. These horizons correspond to – scale 1 (2-4 quarters), scale 2 (4-8 quarters) and scale 3 (8-16 quarters), where we treat first scale as the short-term horizon, midterm is represented by the second scale, while third scale stands for the long-term dynamics.

Since we observe the influence of inflation uncertainty on real GDP growth, GDP growth always stands as a dependent variable. Hence, Table 2 presents only descriptive statistics for the wavelet-based GDP growth time-series. It can be seen that all wavelet time-series are stationary, which means that they all oscillate around zero. It is worth of noting that the majority of the wavelet-based GDP growth time-series have kurtosis values higher than the benchmark value of 3. This fact justifies the usage of QR methodology, since Bayesian QR estimator is robust to deviations from normality, meaning that it performs very well in extreme value environment. Jarque-Bera test suggests nonnormality for the majority of the selected time-series.

We do not perform unit root tests, because we operate with the wavelet decomposed series, which are stationary by default.

Table 3 AIC Values for the Selected GARCH Specifications

	Selected countries	*GARCH-norm*	*GARCH-std*	*GARCH-gat*	*GARCH-gev*	*MS-GARCH -norm*
	Australia	78.4	58.4	61.4	79.6	57.3
	New Zealand	65.8	62.7	65.6	88.5	59.7
D1	Japan	45.0	32.3	34.8	45.0	27.9
	South Korea	135.1	127.0	130.2	146.7	119.7
	Indonesia	271.5	258.8	262.7	278.2	263.3
	Australia	204.6	206.8	209.4	215.0	209.6
	New Zealand	180.5	179.6	175.9	187.7	181.2
D2	Japan	77.9	75.7	77.9	94.6	77.2
	South Korea	272.2	269.8	271.2	277.5	265.9
	Indonesia	416.4	412.1	415.8	427.2	419.3
	Australia	351.3	353.7	349.0	346.9	360.1
	New Zealand	277.5	280.0	284.7	277.1	285.4
D3	Japan	202.0	204.4	195.3	209.4	205.7
	South Korea	461.8	464.3	464.1	458.3	464.6
	Indonesia	540.3	542.6	540.0	544.6	541.9

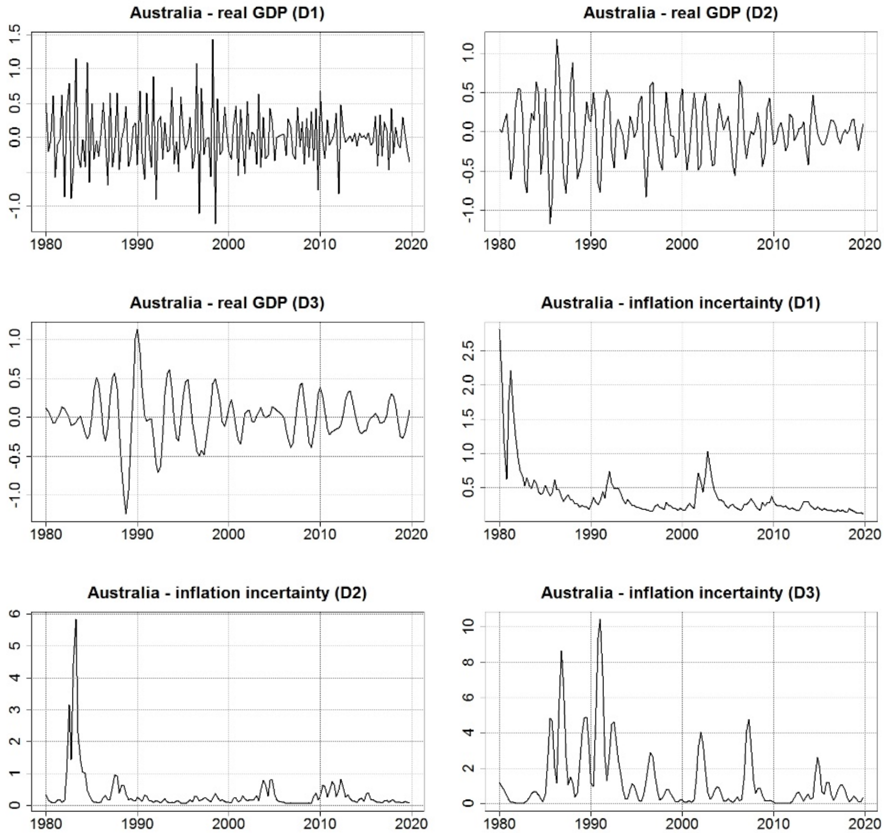
Notes: Greyed values indicate optimal GARCH specification.

Source: Authors' calculation.

The second stage in our three-step procedure involves finding an optimal GARCH specification for the creation of inflation uncertainty time-series. In that process, we consider following distribution functions – normal (norm), Student-t (std), generalized asymmetric Student-t (gat) and generalized extreme value (gev). Besides these distributions, we also estimate Markov switching GARCH (MS-GARCH) model with normal distribution, which can efficiently recognize structural breaks endogenously. In other words, using the wavelet-based inflation time-series, created in the first stage, we estimate different GARCH specification with the sole purpose to find the lowest AIC value. GARCH model with the lowest AIC indicates that it fits best to particular wavelet-based inflation time-series. Accordingly, the best fitting GARCH model is then used for the creation of inflation uncertainty proxy. Table 3 contains AIC values for all the countries and wavelet scales, regarding all the mentioned GARCH specifications. It can be seen that all considered GARCH specification prove optimal for some wavelet-based inflation time-series, which gives us a legitimacy to consider different GARCH models.

Due to space brevity, Figure 2 presents wavelet decomposed series only for Australian real GDP growth and inflation uncertainty proxy. These inflation uncertainty time-series are generated by the optimal GARCH specification from Table 3. Wavelet details of all other countries can be retrieved by request.

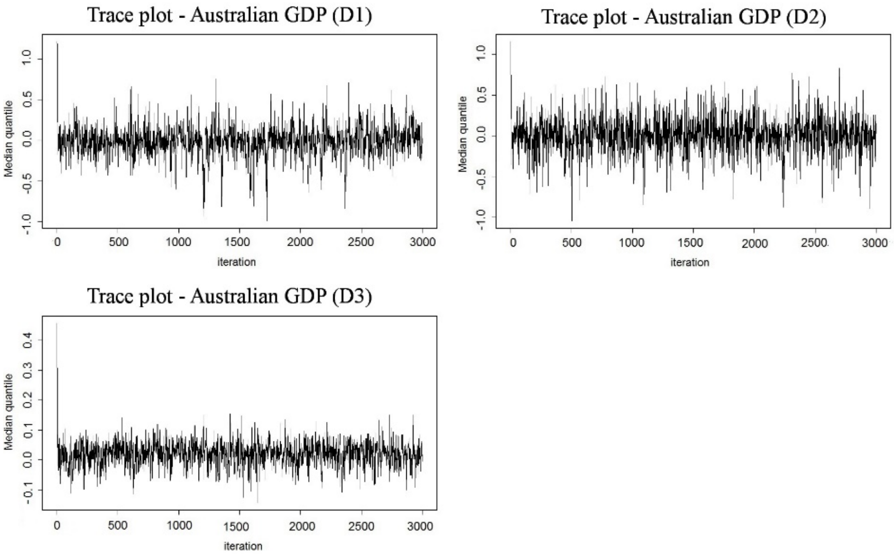
Figure 2 Wavelet Details for Australian Real GDP Growth and Inflation Uncertainty



Source: Authors' calculation.

In the last stage of our three-fold procedure, we embed wavelet-based time-series of real GDP growth and inflation uncertainty in the Bayesian QR framework. The validity of the estimated Bayesian QR parameter can be checked by a visual inspection of the MCMC chains' convergence. These plots show the evolution of the MCMC draws over the iterations. For this research, we use 3000 iterations. Figure 3 displays the trace-plots of the MCMC chain of the wavelet median quantiles, $\hat{\beta}(\tau) = 0.5$, regarding the Australian case.

Figure 3 Trace Plots for the Median Quantile of Australian GDP in Three Wavelet Scales



Notes: The horizontal axis represents the number of MCMC iterations.

Source: Authors' calculation.

It is obvious that all trace-plots have a good performance, which means that the effect of the initial values of the MCMC chains wears off very fast, while the MCMC sampler quickly moves to the stationary distribution. These findings contribute of the trustworthiness of the estimated median Bayesian quantile parameters. Due to the fact that all trace-plots of all other countries across all quantiles are very similar, we portray in Figure 3 only trace-plots for the median quantile of Australian GDP in three wavelet scales, while all other trace-plots can be obtained by request.

5. Research Results

5.1 Full Sample Estimation Results

This section reveals how inflation uncertainty affects real GDP growth in different time-horizons and in different market conditions, taking into account the full sample. Table 4 presents the estimated Bayesian quantile parameters along with the lower and upper bands, which shows the size of the inflation uncertainty impact on real GDP in the periods of market downturn, normality, and upturn. It is interesting to note that an asymmetric effect is well documented in Table 4, which means that left-tail quantiles take negative values, while right-tail quantiles are positive in all the countries and all the wavelet scales. This means that in periods when real GDP records low or negative rates, increased inflation uncertainty has negative effect on real GDP growth. On the other hand, when GDP growth is relatively high, inflation uncertainty has positive influence on the GDP growth. It should be said that it is not uncommon to find mixed evidence about the direction of inflation uncertainty influence on GDP in the extant literature. For instance, Caglayan et al. (2016) investigated the US case between 1960 and 2012, using Markov switching model, and reported that inflation uncertainty exerts negative and asymmetric effects on output growth over the business cycle, whereby this impact is twice as much in low-growth regime than in the high-growth regime. In addition, our results also coincide with the claim of Fountas et al. (2004), who analysed six European countries and disclosed that inflation uncertainty reduces output growth in the UK, while in the Netherlands and Spain, this phenomenon raises real output growth. According to Kočenda and Varga (2018), the link between inflation uncertainty and GDP can also be strengthened from the perspective of inflation persistence, since higher inflation persistence implies smaller monetary policy space to deal with temporary price shocks. This means that higher inflation persistence translates into higher “sacrifice ratio,” which represents the output costs associated with lowering inflation.

However, finding a positive effect of inflation uncertainty on GDP growth might seem counter-intuitive, because higher inflation variability implies increased uncertainty due to less precise inflation expectations, which negatively affect GDP growth. However, this is not always the case. Chowdhury et al. (2018) tried to explain what may lay behind this phenomenon. Investigating the UK and US cases, they contended that cash flows to private sector is low during economic slowdown, while the private firm’s balance sheets are weak, which forces companies to depend considerably on external financial sources. In an increased inflation uncertainty environment, all these factors galvanize companies to delay or even cancel the investment projects. Logical repercussion is reduction in investment, which affects output growth detrimentally. On the other hand, during the period of expansion, cash flows to the firms are relatively high, which makes a favourable situation regardless of the changes in inflation uncertainty. Therefore, in these conditions, companies are willing to finance new investment projects, without worrying what inflation unpredictability might be, which raises an output growth.

Table 4 Bayesian Wavelet-Based Quantile Estimates for the Transmission Effect from Inflation Uncertainty to real GDP Growth – the Whole Sample

Wavelet scales	*Bayesian wavelet-based quantiles with lower and upper bands*														
	Lower	***0.05-th***	***Upper***	***Lower***	***0.25-th***	***Upper***	***Lower***	***0.5-th***	***Upper***	***Lower***	***0.75-th***	***Upper***	***Lower***	***0.95-th***	***Upper***
								Australia							
D1	-2.130	-0.439	0.434	-0.755	-0.121	0.271	-0-385	-0.010	0.371	-0.290	0.129	0.822	-0.392	0.634	2.910
D2	-1.388	-0.263	0.157	-0.524	-0.099	0.177	-0.238	-0.008	0.210	-0.196	0.076	0.484	-0.212	0.274	1.716
D3	-0.490	-0.134	0.063	-0.166	-0.050	0.036	-0.079	-0.004	0.067	-0.055	0.030	0.138	-0.076	0.113	0.482
								New Zealand							
D1	-2.240	-0.245	0.156	-0.261	-0.049	0.171	-0.136	0.037	0.220	-0.079	0.094	0.378	-0.072	0.272	1.520
D2	-0.590	-0.108	0.054	-0.150	-0.028	0.053	-0.093	-0.010	0.074	-0.072	0.010	0.149	-0.081	0.105	0.625
D3	-0.502	-0.124	0.027	-0.150	-0.044	0.045	-0.91	-0.011	0.071	-0.070	0.019	0.154	-0.086	0.097	0.400
								Japan							
D1	-4.520	-0.790	0.789	-1.638	-0.279	0.621	-0.542	0.065	0.798	-0.447	0.363	1.723	-0.609	1.295	5.900
D2	-5.010	-1.151	1.155	-1.826	-0.312	0.485	-0.687	0.071	0.905	-0.448	0.383	1.879	-0.777	1.508	8.950
D3	-0.738	-0.188	0.120	-0.229	-0.036	0.085	-0.109	0.007	0.110	-0.066	0.038	0.196	-0.047	0.276	0.993
								South Korea							
D1	-1.250	-0.317	0.144	-0.390	-0.100	0.084	-0.164	-0.014	0.157	-0.114	0.097	0.448	-0.129	0.301	1.140
D2	-0.809	-0.170	0.120	-0.291	-0.095	0.059	-0.158	-0.013	0.130	-0.097	0.081	0.364	-0.179	0.235	0.783
D3	-0.105	-0.027	0.008	-0.028	-0.006	0.010	-0.012	0.001	0.016	-0.007	0.008	0.027	-0.009	0.023	0.116
								Indonesia							
D1	-0.567	-0.177	-0.019	-0.194	-0.098	-0.005	-0.119	-0.018	0.127	-0.043	0.066	0.179	0.004	0.189	0.513
D2	-0.051	-0.024	-0.003	-0.015	-0.004	0.004	-0.003	0.002	0.007	0.000	0.005	0.011	0.002	0.011	0.034
D3	-0.015	-0.006	-0.001	-0.002	-0.001	0.001	-0.001	0.001	0.002	0.000	0.002	0.004	0.000	0.004	0.011

Source: Authors' calculation.

Table 5 Bayesian Wavelet-Based Quantile Estimates for the Transmission Effect from Inflation Uncertainty to Real GDP Growth – Before Inflation Targeting

Wavelet scales	*Bayesian wavelet-based quantiles with lower and upper bands*														
	Lower	*0.05-th*	*Upper*	*Lower*	*0.25-th*	*Upper*	*Lower*	*0.5-th*	*Upper*	*Lower*	*0.75-th*	*Upper*	*Lower*	*0.95-th*	*Upper*
								Australia							
D1	-2.640	-0.548	0.583	-0.903	-0.079	0.491	-0.424	-0.017	0.458	-0.449	0.092	0.816	-0.672	0.440	2.950
D2	-3.770	-0.365	3.330	0.605	-0.083	0.235	-0.334	-0.022	0.289	-0.273	0.051	0.573	-0.588	0.478	5.830
D3	-0.985	-0.155	0.680	-0.307	-0.057	0.194	-0.139	-0.003	0.133	-0.183	0.047	0.277	-0.646	0.140	0.903
								New Zealand							
D1	-1.576	-0.163	1.155	-0.276	-0.027	0.222	-0.149	0.001	0.153	-0.212	0.034	0.280	-1.191	0.178	2.350
D2	-3.857	-0.578	2.784	-1.109	-0.144	0.821	-0.666	0.013	0.691	-0.753	0.152	1.057	-3.840	0.782	4.451
D3	-2.010	-0.401	1.750	-0.639	-0.083	0.473	-0.841	0.033	0.976	-0.550	0.125	0.701	-3.016	0.792	4.223
								Japan							
D1	-8.160	-0.773	7.610	-1.557	-0.237	0.609	-0.624	0.094	0.946	-0.805	0.404	1.722	-16.660	1.615	18.521
D2	-6.270	-1.189	3.874	-1.204	-0.298	1.106	0.570	0.010	0.583	-1.089	0.256	1.601	-3.415	0.879	4.170
D3	-1.360	-0.109	0.945	-0.201	-0.022	0.290	-0.111	0.005	0.103	-0.178	0.029	0.237	-0.726	0.127	1.030
								South Korea							
D1	-1.651	-0.187	1.190	-0.352	-0.040	0.579	-0.172	0.001	0.179	-0.728	0.069	0.866	-1.522	0.204	1.934
D2	-0.782	-0.077	0.627	-0.797	-0.021	0.603	-0.104	-0.007	0.090	-0.190	0.009	0.208	-0.527	0.079	0.777
D3	-0.489	-0.013	0.492	-0.175	-0.004	0.099	0.009	0.000	0.010	0.098	0.004	0.107	-0.928	0.017	0.962
								Indonesia							
D1	-0.503	-0.163	0.499	-0.229	-0.112	0.223	-0.056	-0.039	0.073	-0.231	0.089	0.187	-0.756	0.190	0.803
D2	-0.854	-0.024	0.651	-0.014	-0.003	0.006	-0.004	0.003	0.007	-0.186	0.006	0.197	-1.280	0.014	1.21
D3	-2.920	-0.012	2.903	-0.480	-0.002	0.476	-0.002	0.000	0.002	-0.628	0.001	0.615	-2.962	0.006	2.958

Source: Authors' calculation.

Table 6 Bayesian Wavelet-Based Quantile Estimates for the Transmission Effect from Inflation Uncertainty to Real GDP Growth – after Inflation Targeting

Wavelet scales	***Bayesian wavelet-based quantiles with lower and upper bands***														
	Lower	0.05-th	Upper	Lower	0.25-th	Upper	Lower	0.5-th	Upper	Lower	0.75-th	Upper	Lower	0.95-th	Upper
								Australia							
D1	-2.910	-0.673	2.007	-1.667	-0.290	1.590	-0.870	-0.065	0.738	-1.257	0.301	1.859	-2.631	1.124	4.188
D2	-2.830	-0.403	2.020	-0.710	-0.086	0.538	-0.468	0.003	0.475	-0.596	0.095	0.786	-1.523	0.225	2.047
D3	-0.847	-0.179	0.486	-0.301	-0.063	0.274	-0.210	-0.025	0.169	-0.237	0.004	0.214	-0.806	0.134	0.852
								New Zealand							
D1	-4.56	-0.561	3.69	-1.210	-0.229	0.961	-0.751	0.076	0.955	-0.572	0.273	1.330	-2.094	0.726	3.950
D2	-1.503	-0.134	1.565	-0.271	-0.029	0.214	-0.180	-0.013	0.154	-0.355	0.012	0.378	-1.384	0.106	1.600
D3	-0.611	-0.116	0.480	-0.156	-0.043	0.152	-0.089	-0.008	0.081	-0.268	0.020	0.307	-0.810	0.121	1.070
								Japan							
D1	-5.400	-1.868	1.659	-1.632	-0.437	0.758	-1.043	-0.171	0.702	-1.197	0.280	1.757	-1.859	1.233	3.959
D2	-3.953	-0.723	2.298	-1.380	-0.100	1.179	-1.243	0.078	1.704	-1.271	0.361	1.665	-2.067	1.096	4.186
D3	-4.090	-1.035	2.135	-1.895	-0.436	1.022	-0.924	0.016	0.890	-0.316	0.379	1.329	-2.041	0.807	3.030
								South Korea							
D1	-7.130	-2.310	0.831	-1.678	-0.330	0.488	-0.715	0.084	1.028	-1.372	0.645	2.662	-3.080	1.670	5.320
D2	-6.031	-2.031	5.197	-1.137	-0.296	0.814	-0.498	0.047	0.663	-1.026	0.563	2.152	-2.814	1.326	3.860
D3	-2.870	-0.379	1.997	-0.465	-0.168	0.591	-0.231	-0.030	0.392	-0.113	0.072	0.550	-1.920	0.368	2.660
								Indonesia							
D1	-1.512	-0.194	1.237	-0.236	-0.034	0.190	-0.134	0.001	0.136	-0.192	0.034	0.261	-1.068	0.169	1.210
D2	-0.510	-0.113	0.384	-0.142	-0.029	0.104	-0.079	-0.003	0.068	-0.126	0.017	0.161	-0.802	0.099	1.000
D3	-1.223	-0.006	1.410	-0.034	-0.000	0.036	-0.001	0.000	0.004	-0.440	0.003	0.445	-1.871	0.008	1.902

Source: Authors' calculation.

This seems as a logical explanation why all estimated wavelet-based 0.75th and 0.95th Bayesian quantile parameters are positive, whereas all 0.05th and 0.25th quantile coefficients are negative. This assertion applies for full sample results as well as for two subsamples (see Tables 4-6).

From the comparative point of view and according to Table 4, inflation uncertainty has the highest effect on real GDP in Japan, while Australia and Korea follow, taking into account the left and right tail QR parameters. However, it should be said that lower and upper confidence intervals of the tail quantiles are pretty wide, so the interpretation of these results can be put in question. This can be seen in Tables 4-6 as well as in Figure 4[7]. The reason why confidence intervals are so broad probably lies in the fact that 0.05th and 0.95th quantiles depict extreme situations, that is, when GDP is very small (negative) or very high, and these situations are very rare taking into account our low-data samples. Due to very small number of observations in the tails of empirical distribution, Bayesian QR needs to broaden confidence intervals in order to preserve reliability of the Bayesian QR parameters. Therefore, from now on, we will pay much more attention on near tail quantile parameters, i.e. 0.25th and 0.75th, which confidence bands are much narrower, and thus much trustworthy.

More specifically, taking into account near tail quantile (0.25th) in short-term horizon (D1 wavelet scale), it can be seen that inflation uncertainty lowers GDP by 29% in Japan, 12% in Australia and 10% in Korea. In addition, it should be said that the effect declines considerably in moderate market conditions, which is represented by the median quantile. As a matter of fact, in these conditions, the effect oscillates around zero in all the countries and in all wavelet scales. Another interesting finding is that inflation uncertainty impact on real GDP is stronger in shorter time-horizons (2-4 quarters), and this applies for all the Asia-Pacific countries, except for Japan. In Japan, we find that the strength of the effect remains preserved up to 4-8 quarters (D2 wavelet scales). For Australia, New Zealand, Korea and Indonesia, these results make sense, because inflation shocks relatively quickly transfer to real economy, hampering in this way the efficient allocation of resources, which mitigates detection of profitable investment opportunities. The final outcome is that output growth is significantly impeded in the short-run. In the longer time-horizons, this effect progressively declines. On the other hand, Japan is somewhat an exception, because Japanese economy has been suffering from extremely low inflation since the mid-1990s, which makes Japanese companies very fearful that low inflation might slip easily into deflation. Probably due to this reason, the effect of inflation uncertainty last longer in the Japanese economy, comparing to all other Asia-Pacific countries.

5.2 Estimation Results of Two Subsamples – Before and After IT strategy

Previous subsection provides average quantile estimates taking into account the full sample. However, this approach is unable to uncover a full truth about the nexus, because it covers two very distinctive periods – before and after IT introduction, which produces significantly different quantile parameters. In other words, since the full sample results comprise the mixed evidence from the two

[7] In order to preserve space, we only plot quantile estimates for the Australian first and second subsamples, while all other quantile plots can be obtained by request.

distinguishing subperiods, this inevitably distorts the final output and leads to unreliable conclusions. In order to resolve this issue, we split the full sample of every country in two subsamples, whereby the referring point is the date of IT implementation. In that sense, Table 5 contains Bayesian QR estimates, taking into account the period before IT, while Table 6 considers the period after IT introduction.

Looking at Tables 5 and 6, it is evident that asymmetric effect is present in both subsamples, which is the similar pattern as in the full sample estimation. In addition, it is obvious that Bayesian quantile parameters differ in a great deal between the two subperiods, and in some instances this divergence is profound. However, the most striking thing that have been found in all the countries is the fact that the effect of inflation uncertainty on the output growth is higher during IT regime, comparing with the period before IT strategy. For example, in the period of economic downturn (0.25^{th} quantile) in the short-run, a 100% increase in inflation uncertainty lowers GDP growth by 7.9% in Australia in the first subsample, while in the second subsample, after IT is implemented, this effect amounts 29%. In the cases of New Zealand and South Korea, this discrepancy is even more pronounced. In the first subsample, this effect is 2.7% and 4% for New Zealand and South Korea, respectively, while in the second subsample, this impact is 22.9% and 33% for these two countries, respectively. In the case of Japan, the effect of inflation uncertainty on GDP is the strongest, taking into account both subsamples and comparing to all other countries. The negative effect of inflation uncertainty on Japanese GDP amounts 23.7% before IT, while after implementation of IT, this effect is 43.7%. As have been said in the previous section, the reason why we find relatively high negative effect of inflation uncertainty in Japan is the presence of very low inflation in this country since the mid-1990s. Fukuda and Soma (2019) argued that the Bank of Japan tried to overcome a deflationary mindset that lasted for a long time in Japan by announcing 2% inflation target in January 2013. However, despite the unprecedented efforts in monetary easing, the Bank of Japan had serious difficulties in achieving the target and anchor inflation expectations in desirable values. The assertion of these authors coincides very well with our findings. More specifically, due to the fact that Japanese monetary authorities had difficulties to achieve a declared inflation target under IT regime, their failure intensifies inflation uncertainty sentiment among Japanese companies, which consequently produces deeper negative effect on Japanese GDP, than in the period before IT introduction.

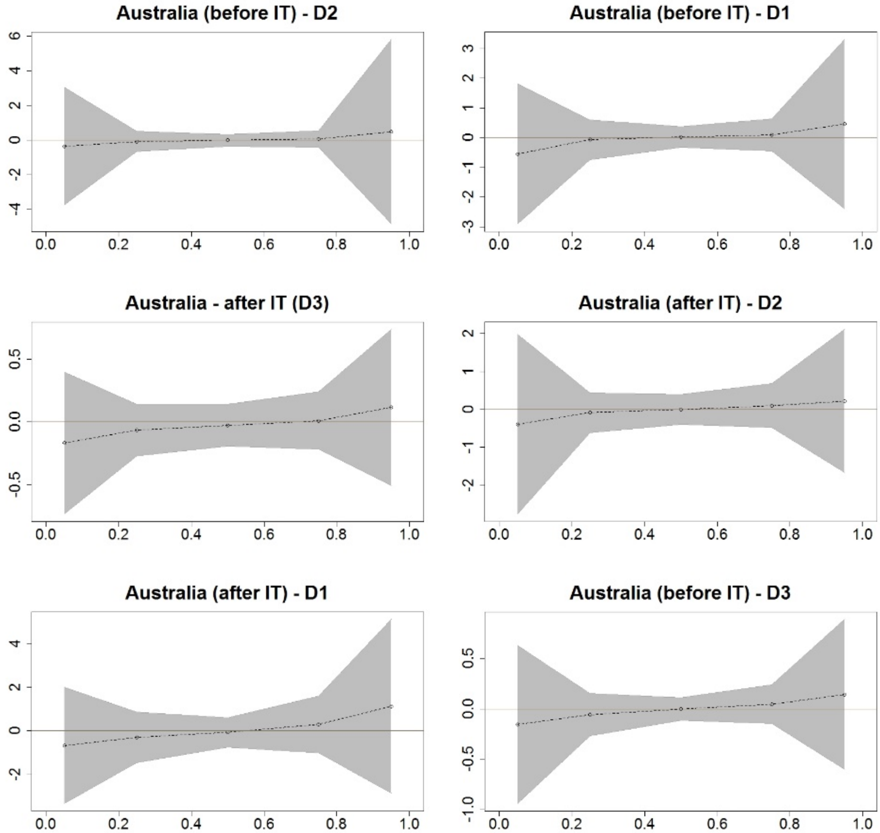
The situation is not much different when the economies are in an upward mode (0.75^{th} quantile). In other words, a 100% increase in inflation uncertainty raises GDP growth by 9.2%, 3.4%, 40% and 6.9% in Australia, New Zealand, Japan and Korea, respectively in the short-run in the period before IT. In the period after IT, these percentages are 30, 27.3, 28 and 64.5 for these five countries, respectively. Therefore, according to the results, it is obvious that our preliminary conjecture, which has been laid in the introduction, is wrong, i.e. inflation uncertainty has greater effect on real GDP growth under the IT regime, than *vice-versa*.

At the first glance, these results may seem puzzling, but at the closer look, there are logical explanation. We find support for our results in the paper of Hartmann and Roestel (2013). These authors asserted that in economies, which are characterized by well anchored inflation expectations, output growth is more strongly affected by excess inflation, than in the systems which are not based on prudent disinflationary policy. In other words, under the inflation targeting regime, which is based on transparency and reliability, every derailment from the expectations that private sector has about inflation, produces more adverse effects on output growth, than in the regimes which have not well-grounded anti-inflationary policy. This is all about expectations, i.e. if private sector does not expect high inflation, and it happens, it produces more severe effect on output, than in the cases when public does not have high expectations about inflation stability. If inflation shocks are expected, then companies are prepared for possible inflation surprises, and this does not inflict much harm to GDP growth. By splitting full sample into two subsamples, before and after IT, we create just such situations in which public expectations about inflation stability are – 1) not high (before IT) and 2) high (after IT).

This effect also goes in the opposite direction, i.e. it raises GDP growth disproportionally high in the periods of economic expansion in the conditions in which monetary authorities put greater effort to guarantee inflation stability (period after IT). Conversely, this effect is much lower in no IT regimes, which means that, in these conditions, public is aware that sudden inflationary shocks may happen anytime, thus a strong positive impact on GDP gets short.

As for the Indonesian case, the estimated quantile parameters do not show strong disparity between the regimes. As a matter of fact, we find that inflation uncertainty has slightly higher negative effect on real GDP growth in the period before IT in the short-run (-11.2%) at 0.25^{th} quantile, than in the period after IT (-3.4%). The same situation is in the period of economic growth (0.75^{th} quantile), i.e. the estimated parameters are then 8.9% vs 3.4%. The results for Indonesia may seem bewildering, because this country conducts IT since July 2005, which raises a question why the results for Indonesia are so different comparing to the results of other four IT countries. The paper of Taguchi and Kato (2011) may provide an answer for this question. They contended that although Indonesia conducts IT policy, the Indonesian strategy is backward-looking. They explained that private sector makes inflation expectations much easier when central bank shares reliable inflation-forecasting information with the public in the forward-looking framework. On the other hand, the backward-looking rule could be frequently accompanied by unreliable inflation forecasting, which makes much harder for private agents to recognize the true intentions of central bank, regarding anti-inflationary measures. Therefore, it could be argued that Indonesian private sector does not have too high expectations about inflation stability, although Indonesia is in IT regime since 2005. Because of that, if inflation shocks occur, Indonesian public is well accustomed to these shocks, which, in turn, do not leave too much consequences on Indonesian GDP growth, either positive or negative. Table 1 in the introduction supports this claim. It shows that although Indonesia halved inflation after IT introduction, average inflation is still relatively high, amounting over 6%, which means that expectations about high inflation are well rooted in the Indonesian society. In these circumstances, there is not much room for inflation uncertainties to significantly raise or low real output growth, because relatively high inflation is a part of Indonesian every-day life. Relatively low tail quantile parameters in Tables 5 and 6 clearly confirms this contention.

Figure 4 Australian Wavelet-Based Bayesian QR Parameters – before and after IT



Notes: The shaded area gives the adjusted credible intervals at 95 percent probability.
Source: Authors' calculation.

6. Conclusions

This paper tries to determine how inflation uncertainty affects real GDP growth in five Asia-Pacific countries – Australia, New Zealand, Japan, South Korea and Indonesia. Due to the fact that these countries adopted inflation targeting strategy at some point in time, we want to determine whether and how inflation uncertainty impacts output growth in two distinctive subperiods – before and after IT. In addition, we strive to find out what is the nature of this effect in different time-horizons and in different market conditions. In this respect, we apply wavelet methodology, construct accurate measure of inflation uncertainty proxy and use Bayesian quantile regression, which produces robust parameter estimates.

The following results can be highlighted. We find an asymmetric effect in full sample as well as in two subsamples, meaning that inflation uncertainty negatively affects real GDP growth in periods of economic contraction, while this nexus is positive in the periods of economic expansion. In addition, the results indicate that this effect is notably stronger in the period after IT than in the period before IT. This finding particularly applies for Australia, New Zealand, Japan and Korea, which conduct well-established IT strategy. These results indicate that if country pursue reliable anti-inflationary policy, output growth is more strongly affected by excess inflation uncertainty, than in the systems which are not based on a prudent disinflationary policy. As for the case of Indonesia, the impact of inflation uncertainty to real GDP growth is very similar in both subsamples, although this country conducts IT policy since July 2005. The rationale for this finding probably lies in the fact that Indonesia favours IT strategy that is backward-looking. However, this strategy is frequently found unreliable, with not too high expectations about inflation stability. This generates too much room for unexpected inflationary shocks, to which Indonesian public is used to. Therefore, in this type of environment, inflationary shocks do not leave too much consequences on Indonesian GDP growth, either positive or negative, and this is the reason why quantile parameters are relatively unison, taking into account both subsamples.

As for the policy perspective, the implications are following. It could be concluded from the results that inflation uncertainty produces significant harm to output growth, for economies that put a high effort on keeping inflation low, in the periods of economic contraction. This implies that monetary authorities of these countries need to keep inflation stable and low as much as possible. On the other hand, in economies which have well-rooted expectations about high inflation, sudden inflationary shocks do not cause too much damage to real GDP growth.

This paper could be interesting for policymakers of the selected Asia-Pacific countries as well as for wider audience, because it brings some new and reliable answers in the respect of how inflation uncertainty affects output growth in the periods before and after IT as well as in the different time-horizons. In addition, the quality of this paper also lies in the fact that it offers reliable results, which is accomplished by the use of the several novel and elaborate methodologies.

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