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ScienceDirect
Physica A 375 (2007) 265–273
PHYSICA A
www.elsevier.com/locate/physa

Effects of adopting inflation targeting regimes on inflation variability

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Received 21 April 2006
Available online 11 September 2006

Abstract

This paper investigates whether inflation-targeting programs have altered the pattern of inflation and its variability for five developed countries and four emerging economies implementing inflation-targeting programs. A GARCH specification is used to model inflation variability, which accounts for public perception of the future levels of inflation variability—conditional variance. We could not find lower conditional inflation expectations except for Australia, Chile and Sweden under various specifications. Moreover, the conditional variance decreases only for Chile and the UK. Therefore, the empirical support for the lower inflation and its variability for the inflation targeting regimes is limited.

Keywords: GARCH; Inflation targeting and inflation variability

1. Introduction

In the 1990s, the monetary policy concerns of many countries changed in the direction of low and stable inflation with the purpose of economic growth, low inflation uncertainty and growth sustainability. Therefore, many developed and developing countries started to adopt inflation-targeting programs to improve their economic performance. Although inflation-targeting programs have been mostly successful in achieving the targeted inflation levels, there are various debates on the performance of these programs.

One of these discussions is about the effect of inflation-targeting programs on inflation variability. It is valuable to analyze the behavior of inflation uncertainty because it affects macroeconomic variables such as output, investment, interest rate. For example, Friedman [1], Froyen and Waud [2] and Holland [3], argue the presence of the adverse effect of inflation uncertainty on output; Hafer [4] and Holland [5] elaborate on the negative effect of inflation uncertainty on employment; Berument [6] shows that inflation variability raises UK's 3-month treasury-bill rates.

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0378-4371/$ - see front matter
doi:10.1016/j.physa.2006.08.047

There is contradictory evidence about the performance of inflation-targeting programs in achieving lower inflation volatility. Some studies claim that the adoption of inflation-targeting programs does have an impact on reducing the inflation variability, while some argue that this effect is not present.

Regarding inflation uncertainty, some argue that inflation variability and inflation expectations decrease after the adoption of inflation-targeting programs. Dittmar et al. [7] and Gavin [8] elaborated on the performance of these programs in reducing the volatility of inflation. The former study gives evidence from G-10 countries about the behavior of inflation and its variance, and then explains analytically how inflation-targeting programs can be successful in decreasing inflation variability. Gavin [8] further supports this proposition by reviewing the experience of other inflation-targeting countries.

Some studies assert that, in the inflation-targeting countries, a decrease in the inflation expectations and inflation variability should be attributed to the effectiveness of inflation-decreasing programs not to the adoption of inflation targeting regimes. Cecchetti and Ehrman [9] claimed that inflation-targeting programs are not the sole factor in lowering inflation volatility and inflation expectations. Cecchetti and Ehrman [9] discussed both theoretically and empirically on the link between inflation variability and output volatility under inflation-targeting programs. In this study, data is used from 9 inflation-targeting countries (Australia, Canada, Chile, Finland, Israel, New Zealand, Spain, Sweden, the UK) and 14 non-inflation-targeting countries (Austria, Belgium, Denmark, France, Germany, Ireland, Italy, Japan, Korea, Mexico, Netherlands, Portugal, Switzerland, the US). They argued that the monetary policymakers in these countries preferred to take actions that favor a reduction in the volatility of inflation compared to a drop in output volatility. Thus, it is not the inflation-targeting programs but the general tendency of the policymakers to reduce inflation that can be considered the main reason for the drop in the level of inflation in the countries analyzed (see, for example, [10–14] for further support of this issue).

Two of the other studies ([15,16]) elaborated on the effectiveness of inflation-targeting programs on inflation uncertainty. In these works, Johnson used inflation surveys of experts to measure the expected inflation and variability of inflation and showed that an inflation-targeting regime decreases the level of expected inflation; however, the variability of inflation forecast errors does not decrease significantly in the targeting countries (Australia, Canada, New Zealand, Sweden, the UK) compared to not targeting countries (France, Germany, Italy, Japan, Netherlands, the US).

To quantify inflation variability, a variety of measures are employed by different studies, but none of these studies measures the perception of the public on inflation risk. In existing studies in the literature, only the observed variability was measured, only short-run dynamics of the variability were assessed or the measurement of perception was biased. Cecchetti and Ehrman [9] and Dittmar et al. [7] used the deviation of realized inflation from the targeted value as a measure of inflation variability. This type of specification measures observed changes in inflation. In contrast, Johnson [15,16] employed standard deviation of inflation forecasts collected through a survey and conducted among professional forecasters. Although this method is a good measure of variability of expected inflation, as Bomberger [17] argued, survey-based studies have the problem of biased or unreliable data. The people who take part in the survey may be biased, may not give an objective forecast or may not be able to use all the available information. As a result, the standard deviation of these forecasts would not be a reliable measure of the perception toward inflation risk, which is an important measure of the credibility of the program. Another measure of inflation variability, the bivariate stochastic volatility framework, is employed by Arestis et al. [13] and Arestis and Mouratidis [14]. This type of specification is advantageous for modeling inflation-output variability and is designed to evaluate the short-run dynamics of inflation-output variability trade-off but fails to capture the public's perception of the inflation risk.

Unlike the above models, this study uses ARCH/GARCH type of conditional inflation variability specification as a measure of inflation variability. This specification measures the perception of the public on inflation variability rather than the variance itself. Inflation uncertainty series are examined to determine whether inflation-targeting programs have a significant effect on the evolution of inflation variability. In this way, we will be able to see whether inflation-targeting programs can really convince the public in the variability of inflation has been reduced. This is the contribution of this study to the existing literature, in which public perception has not been considered before.

To perform this analysis, five developed countries (Australia, Canada, New Zealand, Sweden, the UK) and four emerging economies (Brazil, Chile, Colombia, South Africa), which implement inflation-targeting programs were selected.[1] The analysis of both developed and developing country data will serve as a basis for the comparison of these two groups with respect to the efficiency of the inflation-targeting programs in reducing the inflation variability if there is any discrepancy. The Section 2 will explain the methodology used in this work. Then in Section 3, empirical evidence will be given. Section 4 is the conclusion.

2. Methodology

In order to model inflation, we used an nth order autoregressive process, AR(n)[2]:

$$\pi_t = \beta_0 + \sum_{i=1}^{n} \beta_i \pi_{t-i} + \varepsilon_t, \tag{1}$$

where π_t is the inflation level at time t, n is the number of lags, ε_t is the residual term at time t. Here, inflation has an autoregressive expression at the lag length of n to account for the effect of autocorrelated residuals and we assume that ε_t has a zero mean and time-varying variance of h_t^2. To model the time varying variance, Engle [18], used autoregressive conditional heteroscedastic (ARCH) model, which is a conditional variance of the inflation equation

$$h_t^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2. \tag{2}$$

Later, Bollerslev [21] included past values of h_t^2 in addition to the lagged values of the squared residuals to capture the conditional variance—generalized autoregressive conditional heteroscedasticity model: GARCH (p,q).

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} h_{t-i}^2 + \sum_{j=1}^{q} \alpha_{2\mathrm{j}} \varepsilon_{t-j}^2. \tag{3}$$

In this specification, two points need attention as sufficient conditions; firstly due to the non-negativity property of variances, the constant and the coefficients should be positive (α_0, α_{1i}, $\alpha_{2i} > 0$, for all i, j). Secondly, conditional variance should not explode; hence, to provide non-explosiveness, the sum of the coefficients except the constant should be less than 1:

$$\sum_{i=1}^{p} \alpha_{1i} + \sum_{j=1}^{q} \alpha_{2j} < 1.$$

In the literature, studies exist that also include some exogenous variables in the GARCH specification; for instance, Karolyi [22] included variance of stock market yields of foreign countries to model the variance of stock market yields of the home country. As another example, Berument and Kiymaz [23] and Kiymaz and Berument [24] included daily dummies to stock market returns and its conditional variance to account for the day of the week effect in stock market conditional variance. With this in mind, in this study, we included some exogenous variables in the mean inflation and GARCH equations to capture the impact of inflation-targeting programs on inflation volatility.

To differentiate the periods before and after the inflation-targeting program adoption, an exogenous dummy variable is used to represent the time of implementation. The dummy variable d_t takes the value of one

[1] Mexico is also included in the analysis in the initial step; however, the results of the estimation changed according to the sample used for this country. Due to the instability of the Mexican estimates, Mexico was eliminated from the study.

[2] Parallel to earlier studies like Refs. [18–20], we selected the autoregressive process to model inflation. In Ref. [6], also included real wage as an explanatory variable in the inflation specification for the UK, but it was found to be statistically insignificant. Hence, we do not use other variables such as real wages in the inflation specification in order to avoid over-parameterization. It might have been possible to include additional variables for the nine countries that we considered. However, the models would likely not include the same variables for the inflation specification for the nine countries. Thus, we did not pursue this avenue further for the parallelism.

for the periods that inflation targeting is adopted, zero otherwise. In addition to this dummy, eleven monthly dummy variables are included to account for the seasonality in inflation. Thus, the new inflation equation, formed by employing the dummy variables (mean equation), is as follows:

$$\begin{aligned}\pi_t = {} & \beta_0 + \beta_0^d d_t + \beta_{Jan}^d d_{Jan,t} + \beta_{Feb}^d d_{Feb,t} + \beta_{Mar}^d d_{Mar,t} + \beta_{Apr}^d d_{Apr,t} \\ & + \beta_{May}^d d_{May,t} + \beta_{Jun}^d d_{Jun,t} + \beta_{Jul}^d d_{Jul,t} + \beta_{Aug}^d d_{Aug,t} + \beta_{Sep}^d d_{Sep,t} \\ & + \beta_{Oct}^d d_{Oct,t} + \beta_{Nov}^d d_{Nov,t} + \beta_{Dec}^d d_{Dec,t} + \sum_{i=1}^{n} \beta_i \pi_{t-i} + \varepsilon_t, \end{aligned} \tag{4}$$

where $d_{Jan,\ t}$ to $d_{Dec,\ t}$ are the monthly seasonal dummy variables equal to one for the respective months and zero for the others.

In order to estimate the inflation equation shown by Eq. (4), three different GARCH specifications are employed separately: The first one is the GARCH (1,1)[3] model, in which no differentiation is made for inflation targeting periods, given below

$$h_t^2 = \alpha_0 + \alpha_1 h_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2. \tag{5}$$

The second model has an additive dummy variable for the inflation targeting era inserted in the GARCH (1,1) specification, in order to see if there is an exogenous decrease in the conditional variance of inflation:

$$h_t^2 = \alpha_0 + \alpha_0^{\mathrm{d}} d_t + \alpha_1 h_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2. \tag{6}$$

In the third conditional variance expression, besides the additive dummy variable (used for inflation targeting period) two multiplicative dummy variables were included. The first multiplicative dummy is employed with the lagged conditional variance, the second one is used with the lag of squared residual term. In this way, we are able to observe the behavior of persistence and impulse variability of inflation, respectively, after the inflation targeting is adopted. This last conditional variance equation is given as follows:

$$h_t^2 = \alpha_0 + \alpha_0^d d_t + \alpha_1 h_{t-1}^2 + \alpha_1^d d_t h_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 + \alpha_2^d d_t \varepsilon_{t-1}^2. \tag{7}$$

3. Empirical evidence

Before modeling inflation with GARCH specification, we will check whether the inflation series has an ARCH effect. Hence, the ARCH-LM test is performed for the inflation targeting countries concerned. First, the inflation series of each country is regressed on a constant, 11 monthly dummy variables and the inflation lags, where final prediction error criteria (FPE) is applied to determine the optimum number of lags for which the autocorrelation existing in the residuals of the inflation equation is eliminated.[4] After that, the residuals of this regression are squared and regressed on constant and lagged squared residuals. Here, the number of lags for residuals, which are the regressors, are chosen arbitrarily as 3, 6, 12, 18 and 24. Table 1 reports the p-values of these regressions for each inflation targeting country.

The null hypothesis of 'there is no heteroscedasticity' is rejected for all the countries for the 3 and 6 lags at 1% level. We could not reject the null only for New Zealand at 18 and 24 lags and at the 5% level for the remaining lags. Thus, we assume that the ARCH effect exists for all the countries that we consider.

In the next step, the variability of the inflation residuals is modeled with a GARCH specification. Table 2 reports the estimation results of the first model, specified with Eq. (4) for the mean inflation and Eq. (5) for the conditional variance. In this table, the coefficient of the dummy variable for the inflation targeting period, β_0^d,

[3]We could also employ different GARCH orders or ARCH type of classifications. There are two reasons for not doing so. First, GARCH (1,1) is the most commonly used specification for the conditional variances in general. Second, a set of robustness statistics that we performed on GARCH (1,1) specification provides evidence on the adequacy of the specification. We could adopt more complicated models, which would require additional parameters to estimate. In this paper we were able to find limited evidence on the decrease in conditional variance of inflation. It would be more difficult to observe the decrease in conditional variance with more parameters to be estimated.

[4]Jansen and Cosimona [25] argues that ARCH-LM tests of autocorrelated residuals wrongly suggest the presence of an ARCH effect, even when there is no ARCH effect.

Table 1
ARCH-LM test for the inflation series

Country	ARCH-LM(3)	ARCH-LM(6)	ARCH-LM (12)	ARCH-LM (18)	ARCH-LM (24)
Australia	0.000**	0.000**	0.000**	0.000**	0.000**
Brazil	0.000**	0.000**	0.000**	0.000**	0.000**
Canada	0.000**	0.000**	0.000**	0.000**	0.000**
Chile	0.000**	0.000**	0.000**	0.000**	0.000**
Colombia	0.000**	0.000**	0.000**	0.000**	0.000**
New Zealand	0.000**	0.001**	0.034*	0.224	0.552
South Africa	0.000**	0.000**	0.000**	0.000**	0.000**
Sweden	0.000**	0.000**	0.000**	0.000**	0.000**
UK	0.000**	0.000**	0.000**	0.000**	0.000**

**and *indicate 1% and 5% levels of significance, respectively.

Table 2
Estimation results of the Model 1

Country	β_0^d	α_0	α_1	α_2	Likelihood
Australia	−0.116	3894.642	0.029	0.008	−1018.458
	(0.161)	(447595.088)	(1.801)	(0.981)	
Brazil	0.031	0.061*	0.058	0.674*	36.319
	(0.050)	(0.029)	(0.229)	(0.337)	
Canada	−0.023	0.005	0.875**	0.096**	165.362
	(0.028)	(0.003)	(0.041)	(0.035)	
Chile	−0.288**	0.013	0.771**	0.225**	−106.702
	(0.069)	(0.007)	(0.051)	(0.070)	
Colombia	−0.199	0.000	0.921**	0.076**	−305.753
	(0.102)	(0.001)	(0.020)	(0.024)	
New Zealand	−0.110	0.524**	0.025	0.144	−272.071
	(0.073)	(0.183)	(0.272)	(0.084)	
South Africa	−0.010	0.002	0.948**	0.049*	−176.572
	(0.067)	(0.003)	(0.022)	(0.024)	
Sweden	−0.091*	0.015	0.880**	0.099	26.203
	(0.040)	(0.010)	(0.049)	(0.054)	
UK	−0.030	0.001	0.948**	0.047**	39.465
	(0.033)	(0.001)	(0.015)	(0.016)	

Note: Values in parenthesis show standard deviations of the coefficients.
**and *indicate 1% and 5% levels of significance, respectively.

is negative for all the countries except Brazil, indicating that empirical evidence for Australia, Canada, Chile, Colombia, New Zealand, South Africa, Sweden and the UK is consistent with the expectation that implementation of inflation-targeting program decreases the conditional inflation, but it is only significant for Sweden and Chile. Note that one cannot interpret the estimated coefficient for β_0^d as an indication of lower inflation. Lower steady-state inflation requires that $\beta_0^d/\left(1-\sum_{i=1}^{n}\beta_i\right)$ be negative. Negative β_0^d suggests a lower conditional inflation at a given level of past inflation, which will be called lower conditional expectation from now on. For the coefficients of conditional variance, α_0, α_1 and α_2, the estimation results satisfy the sufficient condition explained in the methodology part for all the countries. That is to say, all of the coefficients are positive (non-negativity) and the sum of α_1 and α_2 is less than 1 (non-explosiveness). The table also reports the

Table 3
Estimation results of the Model 2

Country	β_0^d	α_0^d	α_0	α_1	α_2	Likelihood
Australia	0.075	−4.273	15023.032	0.014	0.080	−896.937
	(0.174)	(2818.614)	(687822.037)	(1.058)	(3.677)	
Brazil	0.023	−0.032	0.083	0.070	0.613*	36.590
	(0.054)	(0.039)	(0.044)	(0.220)	(0.312)	
Canada	−0.021	−0.002	0.008	0.854**	0.100**	165.852
	(0.027)	(0.003)	(0.004)	(0.051)	(0.038)	
Chile	−0.219**	−0.112*	0.133*	0.601**	0.320**	−123.772
	(0.078)	(0.053)	(0.058)	(0.075)	(0.097)	
Colombia	−0.119	−0.001	0.000	0.974**	0.020**	−393.581
	(0.100)	(0.001)	(0.001)	(0.007)	(0.007)	
New Zealand	−0.140	−0.343	0.674	0.022	0.069	−265.269
	(0.073)	(0.219)	(0.400)	(0.532)	(0.066)	
South Africa	−0.110	0.000	0.003	0.935**	0.057*	−157.611
	(0.074)	(0.005)	(0.003)	(0.028)	(0.028)	
Sweden	−0.106*	−0.103	0.152	0.477*	0.212	37.384
	(0.043)	(0.066)	(0.094)	(0.229)	(0.153)	
UK	−0.032	−0.003	0.005	0.920**	0.063**	40.062
	(0.034)	(0.003)	(0.004)	(0.028)	(0.024)	

Note: Values in parenthesis show standard deviations of the coefficients.
**and *indicate 1% and 5% levels of significance, respectively.

log likelihood of the estimations in the last column. We did not report the coefficients of the lagged inflation variables in order to save space. We also calculated Ljung and Box autocorrelation and ARCH-LM tests for the standardized residuals (ε_t/h_t) for various lags for the current and other specifications that are used in this paper. These test statistics are reported in the Appendix. Even if the ARCH-LM test fails to reject the ARCH effect for Chile and Colombia, after allowing conditional variance to change with adoption of inflation targeting regimes, this problem is mostly eliminated. Overall, we could reject the presence of autocorrelation and heteroscedasticity for our specifications. This further supports the validity of our specifications.

After estimating inflation volatility using the general GARCH (1,1) specification, the second model is estimated, in which the conditional variance equation has an additive dummy variable for the periods of inflation targeting, as well. Table 3 reports the estimations of the second model as specified by Eqs. (4) and (6). The estimated coefficient for β_0^d is negative again for all the countries except Australia and Brazil. For the remaining countries, although the effect of the program is as expected (negative), β_0^d is significant just for Chile and Sweden. When we look at the effect of the dummy for the inflation targeting period on the conditional variability of inflation, α_0^d, it is negative for all except South Africa, illustrating that conditional inflation variability decreases after the implementation of an inflation-targeting program, but it is significant only for Chile. Table 3 also reports the values of the coefficients of conditional variance equation, α_0, α_1 and α_2, and the log likelihood of the estimation. As explained in Section 2, the non-negativity and non-explosiveness conditions are satisfied, which is required for a good estimation.

Eqs. (4) and (7) form the specifications of our third model, in which conditional variance of inflation includes multiplicative dummies in addition to the additive dummy for the inflation-targeting period. Table 4 reports the estimation results of the third model. The impact of the inflation-targeting dummy variable in the mean inflation, β_0^d, is negative for all countries but only significant for Australia, Chile and Sweden. Therefore, it can be said that inflation-targeting programs reach their goals to some extent; that is, the conditional expectation of inflation decreases during the inflation-targeting period. When the effect of the additive dummy variable on the conditional variance of inflation, α_0^d, is analyzed, it is negative for all except Canada, Colombia

Table 4
Estimation results of the Model 3

Country	β_0^d	α_0^d	α_1^d	α_2^d	α_0	α_1	α_2	Likelihood
Australia	-1.236^{**} (0.446)	−79.808 (64146.658)	0.051 (2.123)	0.278 (26.502)	28108.384 (2668281.173)	0.045 (1.818)	0.283 (26.965)	−957.532
Brazil	−0.019 (0.048)	−0.168 (0.148)	0.634 (0.669)	−0.022 (0.487)	0.218 (0.144)	−0.504 (0.553)	0.421 (0.353)	38.717
Canada	−0.033 (0.028)	0.081^{**} (0.023)	-1.066^{**} (0.160)	0.213 (0.176)	0.002 (0.002)	0.919^{**} (0.033)	0.071^{*} (0.031)	167.805
Chile	-0.268^{**} (0.079)	-0.318^{**} (0.095)	0.791^{**} (0.114)	-0.788^{**} (0.262)	0.321^{**} (0.095)	0.139 (0.104)	0.821^{**} (0.264)	−118.174
Colombia	−0.174 (0.100)	0.062 (0.061)	−1.163 (1.077)	−0.019 (0.149)	0.002 (0.002)	0.958^{**} (0.014)	0.034^{*} (0.014)	−390.401
New Zealand	−0.143 (0.073)	−0.297 (0.766)	−0.147 (1.452)	0.041 (0.143)	0.670 (0.642)	0.043 (0.871)	0.049 (0.075)	−265.223
South Africa	−0.103 (0.075)	0.028 (0.064)	−0.283 (0.431)	0.181 (0.293)	0.003 (0.003)	0.939^{**} (0.027)	0.054^{*} (0.027)	−156.489
Sweden	-0.109^{*} (0.043)	−0.071 (0.102)	−0.405 (0.295)	−0.001 (0.324)	0.191 (0.111)	0.342 (0.278)	0.257 (0.195)	38.884
UK	−0.034 (0.036)	-0.334^{**} (0.129)	0.254 (0.468)	0.322 (0.307)	0.372^{**} (0.130)	−0.175 (0.266)	0.120 (0.077)	33.972

Note: Values in parenthesis show standard deviations of the coefficients.
**and *indicate 1% and 5% levels of significance, respectively.

and South Africa. Importantly for the UK and Chile, the negative effect of the inflation-targeting program on the variability of inflation is significant; however, for Canada, the positive effect of inflation-targeting program is significant. Hence, the conclusion can be drawn that inflation-targeting programs do not have a uniform effect on the variability of inflation.

Not only the level of variance but the persistence of variance might be affected by inflation targeting. If the coefficient of ε_{t-1}^2 decreases, this suggests that impulse variability decreases. If the coefficient of h_{t-1}^2 decreases, then what we call the memory of shock also decreases. Accordingly, for Canada, Colombia, New Zealand, South Africa and Sweden, the effect of the multiplicative dummy with the lagged value of conditional variance, α_1^d, is negative, which indicates that the persistence of inflation variability decreases during the inflation targeting period but it is significant only for Canada. However, for the case of Chile, the persistence of inflation volatility during the inflation targeting period is positive and significant.

The other multiplicative dummy used with the lag of squared residual, α_2^d, has a negative influence on the inflation variability of Brazil, Chile, Colombia and Sweden but is significant only for Chile. This negative coefficient suggests that the impulse variability of inflation decreases during the inflation targeting period in these countries. When the values of the remaining coefficients (α_0, α_1 and α_2) are analyzed, although the non-explosiveness requirement is satisfied for all the countries, the non-negativity requirement is not fulfilled for Brazil and the UK. We did not explore this further since (i) the added interactive terms were not statistically significant and (ii) when they were dropped, the conventional restrictions were satisfied (see Table 3). The last column displays the log likelihood of the estimation.

Lower and statistically significant evidence is observed for Chile and the UK for the conditional variance. This could not be generalized for other inflation targeting countries. Therefore, we claim that lower variability is not observed for all the inflation targeting countries. This is similar to the results of Johnson [15,16] and others.

4. Conclusion

This paper examines whether inflation-targeting programs altered the pattern of inflation and its variability for the five developed country and the four emerging economies that have implemented inflation-targeting programs. We could not find lower conditional inflation expectations except for Australia, Chile and Sweden under various specifications. Moreover, the conditional variance decreased statistically significantly only for Chile and the UK. Therefore, the empirical support for the lower inflation and variability for the inflation targeting regimes is limited.

Appendix

For the specification tests of Models 1–3, see Tables A1–A3.

Table A1
Specification tests of the Model 1 (*p*-values)

	Panel A: Autocorrelation tests				Panel B: ARCH-LM tests			
Country	AR(6)	AR(12)	AR(24)	AR(36)	ARCH-LM(6)	ARCH-LM(12)	ARCH-LM(24)	ARCH-LM(36)
Australia	1.000	0.313	0.853	0.776	0.986	0.821	0.999	1.000
Brazil	0.733	0.466	0.856	0.295	0.961	0.946	0.968	0.988
Canada	0.952	0.989	0.748	0.764	0.935	0.962	0.997	1.000
Chile	0.136	0.420	0.037*	0.174	0.000**	0.000**	0.999	1.000
Colombia	0.960	0.967	0.825	0.556	0.906	0.000**	0.000**	0.000**
New Zealand	0.974	0.990	0.994	0.846	1.000	1.000	1.000	1.000
South Africa	0.973	0.926	0.185	0.214	0.689	0.907	0.732	0.851
Sweden	0.780	0.785	0.681	0.361	0.925	0.822	0.977	0.922
UK	0.728	0.835	0.476	0.372	0.928	0.976	0.999	1.000

**and *indicate 1% and 5% levels of significance, respectively.

Table A2
Specification tests of the Model 2 (*p*-values)

	Panel A: Autocorrelation tests				Panel B: ARCH-LM tests			
Country	AR(6)	AR(12)	AR(24)	AR(36)	ARCH-LM(6)	ARCH-LM(12)	ARCH-LM(24)	ARCH-LM(36)
Australia	1.000	0.929	0.980	0.983	0.970	0.818	0.999	1.000
Brazil	0.725	0.490	0.851	0.294	0.966	0.915	0.985	0.997
Canada	0.965	0.989	0.772	0.746	0.925	0.928	0.998	1.000
Chile	0.794	0.835	0.058	0.201	0.668	0.842	0.303	0.632
Colombia	0.682	0.649	0.277	0.130	0.961	0.000**	0.000**	0.000**
New Zealand	0.996	1.000	0.999	0.975	1.000	1.000	1.000	1.000
South Africa	0.956	0.949	0.215	0.217	0.808	0.947	0.918	0.989
Sweden	0.820	0.865	0.361	0.236	0.940	0.751	0.794	0.663
UK	0.744	0.797	0.532	0.434	0.796	0.930	0.998	1.000

**and *indicate 1% and 5% levels of significance, respectively.

Table A3
Specification tests of the Model 3 (*p*-values)

	Panel A: Autocorrelation tests				Panel B: ARCH-LM tests			
Country	AR(6)	AR(12)	AR(24)	AR(36)	ARCH-LM(6)	ARCH-LM(12)	ARCH-LM(24)	ARCH-LM(36)
Australia	0.999	0.999	0.944	0.979	0.809	0.746	0.999	1.000
Brazil	0.704	0.406	0.755	0.191	0.990	0.959	1.000	1.000
Canada	0.905	0.981	0.670	0.663	0.907	0.962	0.994	1.000
Chile	0.978	0.927	0.179	0.447	0.692	0.739	0.669	0.934
Colombia	0.718	0.728	0.406	0.262	0.949	0.000**	0.000**	0.000**
New Zealand	0.996	1.000	0.999	0.974	1.000	1.000	1.000	1.000
South Africa	0.967	0.932	0.204	0.194	0.760	0.933	0.888	0.982
Sweden	0.857	0.870	0.559	0.393	0.991	0.967	0.995	0.867
UK	0.225	0.226	0.091	0.026*	0.175	0.053	0.174	0.347

**and *indicate 1% and 5% levels of significance, respectively.

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