Economic Modelling 28 (2011) 1424–1434

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/ecmod

Inflation targeting in Latin America: Empirical analysis using GARCH models[☆]

Carmen Broto [*]

DG International Affairs, Banco de España, Alcalá 48, 28014 Madrid, Spain

ARTICLE INFO

Article history:
Accepted 9 February 2011

JEL classification:
C22
C51
E52

Keywords:
Inflation
Inflation targets
Inflation uncertainty
GARCH models
Unobserved component models

ABSTRACT

This paper studies inflation dynamics in eight Latin American countries, some of which have adopted formal inflation targets (IT) as their monetary policy frameworks. We analyze the possible benefits associated with IT, not only in terms of inflation level and volatility, but also regarding other nonlinear characteristics of these series, such as volatility persistence or the fulfillment of the Friedman hypothesis. To describe inflation dynamics we use an unobserved components model, where each component can follow a GARCH type process. Once we estimate the model, the main findings of the empirical exercise confirm the favorable performance of IT.

1. Introduction

A high inflation is costly for any economy, especially for emerging countries, where inflation has been historically more difficult to control than in industrial ones. This is a consequence of the greater influence of exchange-rate fluctuations, food and commodity prices and the uncertainty of agents concerning inflation expectations. Nevertheless, to properly analyze this variable, it is important to focus not only on its level, but also on its volatility. Indeed, a volatile inflation is also costly, as it causes more uncertainty about the future level of inflation. As a result, the more persistent volatility is, defined as the impact of past volatility on current volatility, the higher the costs of a volatile inflation are; see Driffill et al. (1990) for a survey on the costs of inflation. All in all, given the relevance of inflation control for emerging economies, the assessment of the impact of any new monetary policy mechanism on the inflation level and volatility, as well as on the volatility persistence, becomes crucial.

During the last two decades an increasing number of countries have adopted explicit, or formal, inflation targets (IT onwards) as the nominal anchor of their monetary policies. Since New Zealand adopted it for the first time in 1990, one of the reasons of their rapid expansion has been its success in reducing the inflation level and volatility.[1] In particular, inflation control is a relevant topic in Latin America, given the high and volatile inflation rates registered for much of the half of the last century. Since 1990 five Latin American countries have adopted explicit IT, which coincided with a dramatic diminishment of their inflation rates, to one digit in most cases. However, inflation decreased in most countries of the region, irrespective of IT adoption.

As a result of the spreading of formal IT across countries, a large amount of empirical research on the analysis of IT effects on inflation dynamics has grown, although the results are not conclusive. On the one hand, several papers find that IT is a useful tool for the moderation of the level and the volatility of inflation. For example, Kontonikas (2004) or Vega and Winkelried (2005) state that IT helped to reduce inflation rates in different countries, even controlling for past inflation. Nevertheless, their results in terms of persistence are not so conclusive. Gonçalves and Salle (2008) is the first empirical study that focuses on the role of IT in a broad set of emerging countries. These authors state that the choice of IT was beneficial for these economies as it helped to reduce their inflation level and volatility. On the other hand, other authors find that the IT effects are not significant. Their main argument is that the inflation level and volatility also lowered in countries under alternative policy frameworks as a result of a worldwide trend. For instance, Ball and Sheridan (2005) analyze a set of industrial countries and do not observe a clear evidence of performance improvement of the inflation in IT

[☆] The opinions expressed in this document are solely the responsibility of the author and do not represent the views of the Banco de España.

[*] Tel.: +34 91 3388776; fax: +34 91 3386212.
E-mail address: carmen.broto@bde.es.

[1] Nowadays, 23 countries have adopted IT, where 16 of them are emerging; see IMF (2005) or Vega and Winkelried (2005).

0264-9993/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.econmod.2011.02.009

countries with respect to non-targeting countries. Regarding emerging countries, Brito and Bystedt (2010) find the same results by means of a dynamic panel model.

Besides, the literature for emerging countries provides conflicting forecasts regarding the feasible IT effects and its relationship with the credibility of economic policies. From a positive point of view, as the initial credibility of their central banks is low, IT benefits seem to be larger in these countries than in developed ones as a result of their credibility gains (Bernanke et al., 1999; Mishkin and Schmidt-Hebbel, 2007). However, other studies like Sims (2005) warn that the improvements associated with IT are basically rooted on the transparency increase aspect of IT that, if separated from the nominal anchor aspects of IT, could improve policy recommendations. This implies that the lack of an initial credibility could undermine IT performance.

For the specific case of Latin America, the evidence is limited and inconclusive. Among other papers, Corbo et al. (2002) and Schmidt-Hebbel and Tapia (2002) analyze Chile and emphasize the effectiveness of IT to enhance monetary credibility and to diminish the cost of stabilization. Minella et al. (2003) also support the usefulness of IT in Brazil and highlight the reduction in the inflation level and persistence, given the role of IT in the coordination of inflation expectations. On the negative side, Capistrán and Ramos-Francia (2009) point out some caveats about the efficiency of IT in the region and Morón and Winkelried (2005) question IT in highly dollarized economies, like Peru.

In this paper we use a model of the GARCH family to fit inflation and to make an assessment of the IT performance in Latin America exploring certain nonlinear characteristics of inflation. Note that GARCH models have been extensively used in previous empirical literature on inflation since the ARCH model was proposed by Engle (1982), but they have not been much employed to analyze IT. Specifically, we fit the Quadratic STructural ARCH (Q-STARCH) model with seasonal effects proposed by Broto and Ruiz (2009) generalized to allow for interventions that could capture the effects of IT on the inflation mean and variance. This univariate model nests four relevant characteristics of inflation series. Namely, (1) this model distinguishes between dynamics in the short-run and in the long-run; (2) as it is an asymmetric GARCH model, certain volatility features – including volatility persistence or asymmetries – can be characterized; (3) the model has a seasonal component, which avoids possible drawbacks of seasonally adjusted series, and, as already mentioned, (4) we generalize the baseline model to include dummy interventions in the inflation level and volatility. From a technical point of view, this particular model improves previous empirical papers by addressing the role of IT in these four directions simultaneously.

We fit the Q-STARCH model to eight monthly inflation series of Latin American countries, both IT and non-IT. Our objective is to analyze the possible benefits of formal IT mechanisms, not only in terms of lower inflation level and volatility, but also in terms of these nonlinear characteristics of inflation series – such as volatility persistence or asymmetries – that are helpful to make an assessment of IT along these lines, which could be relevant for policy-makers. In general, our findings confirm the favorable performance of IT.

The paper is organized as follows. Section 2 presents the baseline model, the Q-STARCH with seasonality. In Section 3 we describe the inflation series of the eight Latin American economies. Then, in Section 4 we develop the empirical exercise. First, we fit the model to the inflation series, as well as to the pre-targeting and the after-targeting subsamples in IT countries. Afterwards, we generalize our baseline model by including level shift (LS) dummies in the conditional mean and variance equations. Finally, Section 5 concludes.

2. Empirical model: Q-STARCH model with seasonal effects

2.1. The model

Our baseline model is the Quadratic STructural ARCH (Q-STARCH) of Broto and Ruiz (2009) generalized to allow for LS interventions to capture the effects of IT adoption on the mean and the variance. The Q-STARCH model without interventions is as follows. Consider the series of interest, y_t, that can be decomposed into a long-run component, representing an evolving level, μ_t, a transitory component, ε_t, and a stochastic seasonal component, δ_t, with s seasonal periods. In this model, the level follows a random walk, the seasonal component is modeled using a dummy variable formulation and the transitory component is a white noise (Harvey, 1989). The baseline model is given by

$$\begin{aligned} y_t &= \mu_t + \delta_t + \varepsilon_t \\ \mu_t &= \mu_{t-1} + \eta_t \\ \delta_t &= -\sum_{i=1}^{s-1} \delta_{t-i} + \omega_t. \end{aligned} \tag{1}$$

The transitory and long-run disturbances are $\varepsilon_t = \varepsilon_t^\dagger h_t^{1/2}$ and $\eta_t = \eta_t^\dagger q_t^{1/2}$, respectively, where $\varepsilon_t^\dagger$ and $\eta_t^\dagger$ are mutually independent Gaussian white noise processes and h_t and q_t are defined as QGARCH processes that follow these expressions

$$\begin{aligned} h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 \varepsilon_{t-1} \\ q_t &= \gamma_0 + \gamma_1 \eta_{t-1}^2 + \gamma_2 q_{t-1} + \gamma_3 \eta_{t-1}, \end{aligned} \tag{2}$$

where α_0, α_1, α_2, α_3, γ_0, γ_1, γ_2 and γ_3 satisfy the usual conditions to guarantee the positivity and stationarity of h_t and q_t; see Sentana (1995). Finally, the disturbance of the seasonal component is assumed to be a Gaussian white noise with variance σ_ω^2 independent of ε_t and η_t. Under the assumption of Gaussian white noise disturbances ε_t and μ_t, model (1) reduces to the local level model with seasonal component.

Although y_t is non-stationary, it can be transformed into stationary by taking seasonal differences. The stationary form of Eq. (1) is given by

$$\Delta_s y_t = S(L)\eta_t + \Delta\omega_t + \Delta_s \varepsilon_t, \tag{3}$$

where Δ_s and Δ are the seasonal and regular difference operators, $\Delta_s = 1 - L^s$ and $\Delta = 1 - L$, and $S(L) = 1 + L + \ldots + L^{s-1}$. The reduced form of Eq. (1) is an MA(s) model, see Harvey (1989). The Q-STARCH model is in line with other specifications with conditionally heteroscedastic variances that also distinguish between the long and the short-run dynamics; see Kim (1993) or Stock and Watson (2007).

The estimation procedure is based on a quasi maximum likelihood (QML) estimator, as in Harvey et al. (1992). Broto and Ruiz (2006) demonstrate that QML is appropriate to estimate this type of models. Note that even if $\varepsilon_t^\dagger$ and $\eta_t^\dagger$ are assumed to be Gaussian processes, the Q-STARCH model is not conditionally Gaussian, since knowledge of past observations does not imply knowledge of past disturbances. Thus, the QML estimator is based on treating the model as if it were conditionally Gaussian and running the Kalman filter to obtain the one-step ahead prediction errors and their variances to be used in the expression of the Gaussian likelihood given by

$$\log L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T} \log F_t - \frac{1}{2}\sum_{t=1}^{T} \frac{\nu_t^2}{F_t}, \tag{4}$$

where ν_t are the innovations of the Kalman filter and F_t their corresponding variances. We obtain the QML estimator, $\widehat{\Psi}$, by maximizing the Gaussian likelihood in Eq. (4) with respect to the unknown parameters. Before we compute the likelihood in Eq. (4), the Kalman filter also requires analytical expressions of the conditional variances of the disturbances ε_t and η_t in terms of Ψ, that we denote as H_t and Q_t.