Inflation targeting in Latin America: Empirical analysis using GARCH models

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October, 2008

Abstract

During the last years, a number of countries have adopted formal inflation targeting (IT) monetary policy frameworks in a context of global inflation moderation. This paper studies inflation dynamics in eight Latin American countries, some of which have adopted formal targets. We analyze possible benefits associated with IT in terms of lower inflation, inflation volatility and volatility persistence. To describe inflation dynamics and evaluate its impact, we use an unobserved components model, where each component can follow a GARCH type process. In general, the main findings of the empirical exercise show that the adoption of IT has been useful to reduce the inflation level and volatility in these countries.

JEL codes: C22; C51; E52.

Keywords: Inflation targets, inflation uncertainty, GARCH, structural time series models.

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*The opinions expressed in this document are solely responsibility of the author and do not represent the views of the Banco de España. I like to thank Gabriel Pérez Quirós, Esther Ruiz and Enrique Alberola and participants in seminars at LACEA-LAMES meeting in Bogotá and Banco de España for helpful comments received. Corresponding author: Tel: 34 91 3388776; Fax: 34 91 3386212; e-mail: carmen.broto@bde.es. The usual disclaimers apply.

1 Introduction

A high level of inflation is costly for any economy, especially for emerging countries, where historically inflation has been more difficult to control than in industrial countries. Among other factors, this outcome is a consequence of the greater influence of exchange-rate fluctuations, food and commodity prices volatility and the uncertainty of agents concerning inflation expectations. Nevertheless, to properly analyze inflation, it is important to focus not only on its level, but also on its volatility. In general, a volatile inflation is also costly, as it causes more uncertainty about the future level of inflation, which distorts the allocation of resources. Moreover, the more persistent volatility is, defined as the impact of past volatility on current volatility, the higher the costs of a volatile inflation are.[1] All in all, given the relevance of inflation control for emerging economies, the assessment of the impact of any new monetary policy development on inflation, inflation volatility and persistence becomes crucial.

In this context, an increasing number of developed and emerging countries have adopted explicit, or formal, inflation targeting (IT) mechanisms as a nominal anchor for the conduction of monetary policy. One of the reasons of the rapid expansion of this relatively new monetary policy instrument has been its success in reducing the level of inflation since New Zealand adopted it for the first time in 1990.[2] In the case of Latin America, inflation control is a particularly relevant topic, given the high and volatile inflation rates observed for much of the half of the last century. In this context, since 1990 five Latin American countries have adopted explicit IT frameworks. This fact coincided with a dramatic diminishment of their inflation rates, to one digit in most cases, although this inflation decrease also occurred in most countries of the region, irrespective of the adoption of IT.

As a result of the spreading of formal IT mechanisms, there is an increasing field in the literature that evaluates their effects on inflation dynamics, although the results are not conclusive. On the one hand, several papers find that IT is a useful tool for decreasing the level as well as the volatility of inflation. For example, Wu (2004), Kontonikas (2004) or Vega and Winkelried (2005) find that IT did help to reduce inflation rates in different sets of

[1] See Driffill *et al.* (1990) for a survey on the costs of inflation.

[2] Nowadays, 23 countries can be classified as inflation targeting. Seven of them are industrial countries and 16 are emerging; see Vega and Winkelried (2005).

countries, even controlling for past inflation. Nevertheless, the results in terms of persistence of the latter authors are not so conclusive so as to categorically support the effectiveness of IT. On the other hand, some other authors find that the effect of the introduction of an IT mechanism is not significant. Their main argument is that the reduction in the level and volatility of inflation is also present in non-targeting countries as a part of a worldwide trend. For instance, Ball and Sheridan (2003) analyze a set of industrial countries and observe no clear evidence of performance improvement in the inflation of targeting countries with respect to non-targeting countries. In the same line, Johnson (2002), Hyvonen (2004) and Willard (2006) also find small effects of IT mechanisms on inflation by means of different model specifications.

Empirical evidence for emerging countries is even more scarce, although, according to Mishkin and Schmidt-Hebbel (2007), the gains from IT seem to be larger in emerging countries than in industrial ones. Most of previous empirical studies support the usefulness of IT as it implies a higher credibility of the economic policies; see, for example, Truman (2003), Levin *et al.* (2004) and IMF (2005) for more details. For the specific case of Latin America, empirical evidence is also limited and inconclusive. Among other papers, for the case of Chile, Corbo *et al.* (2002) and Schmidt-Hebbel and Tapia (2002) emphasize the usefulness of IT to enhance monetary credibility and to diminish the cost of stabilization. Minella *et al.* (2003) also support IT and highlight the reduction in the level and persistence of inflation in Brazil, given the role of IT in the coordination of inflation expectations. On the negative side, Capistrán and Ramos-Francia (2006) point out some caveats about the efficiency of IT. Finally, Morón and Winkelried (2005) question the role of IT in highly dollarized economies, like Peru.

We propose to use a model of the GARCH family to fit inflation dynamics and to make an assessment of the performance of IT mechanisms in Latin America. Specifically, in this paper we use the Quadratic STructural ARCH (Q-STARCH) model with seasonal effects proposed by Broto and Ruiz (2008) generalized to allow for the presence of interventions to quantify the effects of the introduction of IT on the mean and the variance of inflation. This model nests four characteristics that are highly relevant for the analysis of inflation series, namely, (1) it distinguishes between inflation dynamics in the short-run and in the long-run; (2) as the model is a member of the GARCH family, the volatility dynamics can be fitted and, therefore, (3) the model allows to quantify certain volatility characteristics such as persistence or asymmetry, defined as the different response of volatility to shocks of different sign. Finally, (4) the model is generalized to include dummy interventions to quantify the reduction in the average inflation and volatility of IT countries. That is, from the technical point of view, the use of this specific model improves previous empirical papers by assessing the role of IT in these four directions simultaneously.

In this paper we study inflation dynamics of eight Latin American countries, both inflation targeting and non-targeting, by fitting the proposed Q-STARCH model to both groups of countries. Our objective is to detect possible benefits associated with the adoption of formal IT mechanisms in terms of lower level and volatility of inflation, once the lower rate of inflation that has taken place across the region during the last years is controlled for in the model. The results obtained after model estimation constitute a relevant outcome to make an assessment of the performance of IT in these economies. Although we consider eight countries, our approach is essentially univariate. The study of common dynamics of inflation and volatility by means of a multivariate model is well beyond the scope of this paper. Also note that this paper does not cover causality issues. Thus, as stated by Mishkin and Schmidt-Hebbel (2002), the adoption of IT is an endogenous choice, so that finding a better performance of the economy associated with IT, for instance, in terms of lower level and volatility of inflation, may not imply that IT causes this better performance.

The paper is organized as follows. Section 2 reports a preliminary description of the inflation series of the eight Latin American countries analyzed. Section 3 presents the proposed baseline model for the empirical application, the Q-STARCH model with seasonality. Then, in Section 4 we estimate this model for the inflation series and also for the pre-targeting and the after-targeting subsamples of the five IT countries. Afterwards, we generalize our baseline model by including level shift (LS) dummies in both the conditional mean and variance equations. Finally, Section 5 includes a summary of the main empirical findings and concludes the paper.

2 Inflation in Latin America

In this section, monthly inflation series of eight Latin American countries are preliminarily analyzed. Inflation is measured as the first difference of the monthly non-seasonally adjusted CPI, that is, $y_t = 100 \times \triangle \log(CPI_t)$. As mentioned in the introduction, the sample consists of the five countries with explicit IT mechanisms in the region (Brazil, Chile, Colombia, Mexico and Peru) and three non-targeting countries of the region (Argentina, Ecuador and Uruguay).[3]

Chile was the second country in the world, after New Zealand, and the first country in Latin America that adopted an IT monetary policy regime in September 1990. The central bank combined it with an exchange rate anchor until September 1999, when Chile definitively adopted an explicit IT mechanism after its progressive introduction. Following this pioneering experience, other countries of the region adopted it. For instance, Colombia formally implemented an IT mechanism in September 1999 based on a point target of one year horizon with a symmetric range. Mexico introduced it after the financial crisis of 1995. From 1995 to 1999, the monetary growth target was the nominal anchor of the economy, but, simultaneously, the central bank established IT. Once the uncertainty of the crisis vanished, the central bank became more focused on inflation control. Thus, since 1999 the Mexican central bank is publishing its official targets and in 2001 it explicitly adopted this monetary policy mechanism. Brazil adopted an IT framework in June 1999, after being forced to abandon its crawling exchange rate in January of that year. Finally, Peru adopted IT in 1994, although some studies consider 2002 as the year of adoption of an explicit IT framework, as this target coincided with a money growth operational target.

Dating the adoption of IT in emerging countries is not straightforward. For the sake of homogeneity, in the empirical analysis we use the date of adoption of the explicit IT mechanism for all countries, but for Chile and Peru, where we use the date of IT adoption. In the case of Chile, this second date is mostly used in the empirical literature and, for Peru, we use 1994 as reference date to get more robust estimates for the after-targeting period, as in Corbo *et al.* (2002) or Fraga *et al.* (2003).[4] Table 1 summarizes the dates of adoption of

[3]According to Allen *et al.* (2006), in Latin America there are at present three prospective candidates to adopt explicit IT mechanisms in the near future: Costa Rica, Guatemala and Paraguay.

[4]For Mexico, we use the dating of Vega and Winkelried (2005) or Pétursson (2004), which consider

IT and explicit IT mechanisms.

For each country, we consider the largest sample size available to ensure the convergence of the non-linear optimization algorithm used later on in the estimation. Thus, the largest sample size corresponds to Argentina (1942:2-2006:1), that is, $T = 756$, and the smallest to Ecuador (1995:2-2006:1), with $T = 132$. There is a remarkable difference in the scale of inflation depending on the country: while Argentinean inflation reached historical maxima around 100% by July 1989, inflation in Colombia remained below the two digits inflation across the sample period. To further illustrate the generalized decrease of inflation in recent years, Figure 1 plots the eight series of inflation, y_t, since 1995, together with the dates of IT and explicit IT adoption, if different. This figure accounts for the dramatic diminishment of the inflation level in all countries during the last years compared to the inflation registered at the beginning of the sample. Only in Argentina, during the 2002 crisis, and in Ecuador, around 2000, monthly inflation exceeded two digits.

Table 2 reports a summary of descriptive statistics for the full sample of y_t and for the subsample that begins in 1995:1, as a preliminary analysis of the role of IT in Latin America. Table 2 also shows, for the five countries with explicit IT mechanisms, summary statistics for the pre-targeting and the after-targeting period. These numbers illustrate that the recent inflation reduction has taken place independently of the adoption of an explicit IT, as in all countries the mean inflation is lower in the most recent subsample than in the whole sample. Consequently, even for non-targeting countries, the mean inflation is lower in the most recent period. As mentioned in the introduction, this lower mean inflation has been accompanied by a substantial decrease in the standard deviation of inflation, for both targeting and non-targeting countries.

This rough analysis may lead to the initial conclusion that IT has not played an independent role in the reduction in the level and volatility of inflation, which would coincide with the results of some of the previous literature. Nevertheless, it is possible to extract additional information from inflation level and volatility dynamics by exploiting possible non-linearities present in the data with a suitable model, as the Q-STARCH model presented in the next section, to improve the assessment of the impact of IT. As a first illustration of the presence of these non-linearities that could be suitable fitted by a GARCH type model, Table

January 1999 as the date of adoption of explicit IT framework, instead of January 2001, as in IMF (2005).

3 reports a summary of descriptive statistics of the stationary transformation, $\Delta_{12}y_t$. It shows that inflation data are non-normal, as most series exhibit asymmetry and all of them present excess kurtosis, with kurtosis coefficients running from 4.66 in Colombia up to 21.54 in Argentina.

3 Empirical model: Q-STARCH model with seasonal effects

Our baseline model is the Quadratic STructural ARCH (Q-STARCH) model generalized to allow for the presence of LS interventions to quantify the effects of the introduction of IT on the mean and the variance processes. Note that the models of the GARCH family have been extensively applied in previous empirical analysis of inflation since the ARCH model was proposed by Engle (1982). The model specification 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 specified using a dummy variable formulation and the transitory component is a white noise; see Harvey (1989). The resulting model for y_t 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 defined by $\varepsilon_t = \varepsilon_t^\dagger h_t^{1/2}$ 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 process given by the following 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 the parameters 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 dummy variable.

Note that, at the moment, there is no commonly accepted model in the empirical literature for inflation and, in most specifications, the model is based on capturing a few empirical characteristics of the series. The Q-STARCH model is particularly useful to quantify the effects of implementing IT as it is rather parsimonious and nests some of these stylized facts. For instance, the Q-STARCH model can differentiate between the dynamics in the short and in the long-run, as it is based on an unobserved components model.[5] From the policy-makers' point of view, it is relevant to distinguish if the source of uncertainty comes from the long-run or short-run component. Thus, short-run volatility is most likely to affect temporal policy decisions, whereas uncertainty about the long-run may affect intertemporal decisions, as noted by Kontonikas (2004).

Besides, the model characterizes the evolution of the conditional variance of inflation, as each disturbance can be fitted by a GARCH type model. Consequently, the use of a GARCH model in this way also allows to evaluate certain volatility characteristics such as persistence, defined as the property of momentum in volatility, which can be approximated by $\alpha_1 + \alpha_2$ and $\gamma_1 + \gamma_2$. The Q-STARCH model is in line with other models that distinguish between the long and the short-run dynamics and also consider conditionally heteroscedastic variances; as Kim (1993) or Stock and Watson (2007).

The Q-STARCH model also constitutes a useful tool to study the fulfillment of the Friedman hypothesis (Friedman, 1977), which is tested in our setting by considering an asymmetric GARCH specification for the disturbances of each component.[6] According to this hypothesis, a positive inflation shock would lead to a greater effect on future inflation volatility than a negative one. In other words, "bad news", or higher inflation in our context, have bigger impact on future volatility than "good news", or lower inflation. This asymmetric effect is also known in the financial literature as "*leverage effect*". The identification

[5]See, for example, Ball and Cecchetti (1990) or Grier and Perry (1998) for some other papers that make this distinction.

[6]See Hentschel (1995) for an overview of asymmetric GARCH models and Daal *et al.* (2005) for an application to inflation in emerging countries. Most of these studies strongly support the fulfilment of the Friedman hypothesis.

of this effect in the context of IT is useful for policy-makers, as it also indicates that the dynamics of the level of inflation have an effect on inflation volatility. Thus, if this effect is present in the data and inflation rate lowers, the inflation uncertainty reduction will be more acute, with is an important policy implication. Note that the model defined by (1) and (2) is able to capture these asymmetric ARCH effects in the permanent and/or in the transitory component. That is, the conditional variances in (2) have different responses to shocks of the same magnitude but different sign, so that parameters α_3 and γ_3 will be used to test the fulfillment of the Friedman hypothesis.

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

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

where $\triangle_s$ and $\triangle$ are the seasonal and regular difference operators given by $\triangle_s = 1 - L^s$ and $\triangle = 1 - L$, respectively, and $S(L) = 1 + L + ... + L^{s-1}$. The reduced form of model (1) is an MA(s) model, see Harvey (1989).

The estimation procedure will be 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, Q-STARCH models are 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, $t = 1, ..., T$ are the innovations of the Kalman filter and F_t their corresponding variances. The QML estimator, $\widehat{\Psi}$, is obtained by maximizing the Gaussian likelihood in (4) with respect to the unknown parameters. Before the likelihood in (4) is computed, 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.

4 Empirical analysis

As a preliminary step, we fit model (1) with homoscedastic disturbances to each inflation series to test for the presence of conditional heteroscedasticity in the Latin American series of inflation.[7] In all countries but Brazil, Mexico and Ecuador, the signal to noise ratio, $q = \sigma_\eta^2/\sigma_\varepsilon^2$, is less than one, which means that, in most countries, volatility in the transitory, or short-run component, is higher than in the permanent one. As expected, summary statistics for the estimated innovations, $\widehat{\nu}_t$, strongly suggest the presence of conditional heteroscedasticity as severe excess kurtosis is still present and Ljung-Box statistics for the squared residuals, $Q^2(\tau)$, are significant. This evidence suggests that the baseline Q-STARCH model is a better choice to capture this empirical regularity, instead of the local level model of (1) with homoscedastic innovations.

Next, we identify which component is causing conditional heteroscedasticity: the permanent or long-run component, the transitory or short-run component or both. As proposed by Broto and Ruiz (2008), we use the differences between the autocorrelations of auxiliary residuals and the squared autocorrelations of auxiliary residuals, $\rho_2(\tau) - [\rho(\tau)]^2$, to identify the heteroscedastic disturbances, where the auxiliary residuals are estimates of the disturbances of each component, $\widehat{\varepsilon}_t$, $\widehat{\eta}_t$ and $\widehat{\omega}_t$.[8] In all countries but Colombia and Uruguay, the differences of the autocorrelations of $\widehat{\eta}_t$ show more signs of conditional heterocedasticity than the differences of the short-run component auxiliary residual, $\widehat{\varepsilon}_t$. Therefore, the specification of the long-run component innovation is heteroscedastic in all series but in these two countries. Thus, in all countries but Colombia and Uruguay, empirical results on volatility will refer to long-run inflation uncertainty. This greater volatility dynamics in the long-run component than in the short-run is in concordance with the work by Stock and Watson (2007) on US inflation.

Table 4 reports estimates of model (1) with heteroscedastic disturbances defined in (2).[9] As expected, GARCH parameters are highly significant. Volatility persistence estimated

[7]Estimation of the homoscedastic local level model has been carried out in the program STAMP 6.20 (see Koopman *et al.* (2000)) and is available upon request.

[8]For the sake of brevity, results on these differences are not included in the text but are available upon request.

[9]All these estimations have been carried out using our own FORTRAN codes, which are available upon request.

through the QGARCH specification is defined as $\hat{\gamma}_1 + \hat{\gamma}_2$ for all countries except for Colombia and Uruguay, where it is $\hat{\alpha}_1 + \hat{\alpha}_2$. Volatility persistence is very close to the maximum of one in all countries and runs from the minimum of Brazil (0.87) to the maximum of 0.99 for Chile, Peru and the three non-targeting countries. This means that inflation volatility is quite persistent, although, on average, it is higher in non-targeting countries. Asymmetry parameters, $\hat{\alpha}_3$ and $\hat{\gamma}_3$, are positive and significant for all countries but for Ecuador and Uruguay. Thus, a positive inflation shock has a higher impact on future volatility than a negative one, which confirms the fulfillment of the Friedman hypothesis in the IT countries and Argentina. This results also indicates the presence of a positive link between past inflation and uncertainty about future inflation in these counties. The policy implication is that authorities of these countries have incentives to lower inflation rates to further reduce the costs of a volatile inflation. Summary statistics for the estimated innovations $\widehat{\nu}_t$ presented in Table 4 show that innovations still exhibit excess kurtosis but, in general, Ljung-Box statistics are not significant.

Table 4 also reports estimates for the pre-targeting and the after-targeting period as a first approximation to disentangle the main differences in inflation volatility dynamics of both subsamples.[10] The estimated volatility persistence diminishes in the after-targeting period of all countries but Colombia, where the results are not conclusive, whereas it registers the sharpest decrease in Brazil. The reduction in the volatility persistence is another relevant result that supports the benefits associated with the adoption of IT. The asymmetry parameter estimates, $\hat{\alpha}_3$ and $\hat{\gamma}_3$, are still positive and significant in all countries, except for those of the pre-targeting period in Brazil and the after-targeting period in Chile. This fact confirms that, in general, the Friedman hypothesis is fulfilled for this sample of Latin American countries in both periods.

Finally, Figure 2 plots the estimated volatilities of the heteroscedastic component of each country, which have been obtained by the standardized innovations of the model. In all countries, independently of the adoption of a formal IT mechanism, the first part of the sample is a period of high volatility, whereas in the last years volatility decreases. This moderation of inflation targeters' volatility does not occur necessarily around the date of adoption of the formal IT mechanism. Indeed, the reduction in volatility and the date of

[10]Estimates for the pre-targeting period in Peru could not be obtained due to the lack of data.

IT adoption seem to coincide only in Peru, Chile -that adopted an explicit IT framework in September 1999-, and Mexico. In Colombia, volatility reduction occurred before IT adoption, whereas in Brazil the adoption of IT was followed by an increase of volatility that coincides with the exchange rate depreciation of 2002.

4.1 Measuring the effects of IT on the level of inflation

To properly analyze the impact of the introduction of a formal IT mechanism, it is important to account for possible breaks in the level and volatility of inflation. First, for policy-makers it is crucial to quantify if formal IT adoption significantly affects the mean and the variance of inflation, to make a more precise assessment of the performance of this monetary policy mechanism. Besides, from the technical point of view, neglecting these breaks has undesirable effects on the estimates of the parameters of GARCH type models (see Hillebrand (2005) or Carnero et al. (2007), inter alia). In the next two subsections we will analyze the effects of IT policy frameworks by introducing dummy variables in the mean and in the variance equations of the model, respectively. Thus, in this subsection, the Q-STARCH baseline model of (1) and (2) is generalized to allow for the presence of interventions that capture the effect of the introduction of an IT mechanism on the mean process of inflation.

The model for y_t consists of the same transition equation (1) but now the measurement equation follows this expression

$$y_t = \mu_t + \delta_t + \lambda_L w_t + \varepsilon_t, \tag{5}$$

where w_t represents a LS intervention variable in the level of inflation and λ_L is its corresponding coefficient. The intervention w_t takes value 1 from the moment of the adoption of the explicit IT framework in t_{IT} onwards, that is, during the after-targeting period. Thus, w_t is given by

$$w_t = \begin{cases} 1 & t \geq t_{IT} \\ 0 & t < t_{IT} \end{cases}. \tag{6}$$

Alternatively, w_t could have been specified as an innovative outlier (IO) in the transition equation. Expression (5) simplifies to (1) when $w_t = 0$, that is, when the inflation level is independent of the adoption of an explicit IT. To design w_t, we impose regime changes on a priori grounds for each country. That is, we use the own date of adoption of the explicit IT as t_{IT}, and no structural change test is performed prior to estimation. The conditional variance equations are equal to (2). The estimation procedure is practically the same as for the baseline Q-STARCH model, except for a minor modification in the state vector. Thus, for quarterly data ($s = 4$), the measurement and transition equations needed to design the Kalman filter and obtain QML estimates are, respectively, given by

$$y_t = \mu_t + \delta_t + \lambda_L w_t + \varepsilon_t = \begin{bmatrix} 1 & 0 & 0 & w_t & 1 & 0 & 0 \end{bmatrix} \alpha_t + \varepsilon_t \tag{7}$$

$$\alpha_t = \begin{bmatrix} \mu_t \\ \mu_{t-1} \\ \eta_t \\ \lambda_{Lt} \\ \delta_t \\ \delta_{t-1} \\ \delta_{t-2} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & -1 & -1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \mu_{t-2} \\ \eta_{t-1} \\ \lambda_{Lt-1} \\ \delta_{t-1} \\ \delta_{t-2} \\ \delta_{t-3} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \eta_t \\ \omega_t \end{bmatrix}, \tag{8}$$

where the dynamics of λ_L imply the constancy of the coefficient. The state vector is augmented by lags of μ_t in such a way that the Kalman filter gets estimates of the unobserved disturbances.

Table 5 reports, for the full sample, the estimates of model (5) with heteroscedastic disturbances defined by (2) and summary statistics for the innovations. The estimates are denoted in Table 5 as LO (Level Outlier). Consistently with a reduction in the mean level of inflation after the adoption of an IT framework, $\hat{\lambda}_L$ is negative and significant in Chile, Colombia and Mexico. In particular, the biggest estimate for the level dummy variable coefficient corresponds to Chile with $\hat{\lambda}_L = -1.43$. This outcome is rather intuitive as Chile was the first country of the region in adopting an IT mechanism. Besides, as reported in Table 2, in this country the mean difference between the pre-targeting and the after-targeting period is rather similar to this estimate. In Peru, $\hat{\lambda}_L$ is positive and not significant, whereas in Brazil, $\hat{\lambda}_L$ is not significant either. Note that in Peru and Brazil the differences of mean between both periods, as showed in Table 2, are smaller. This fact may indicate that other characteristics of the series, as the own volatility in the after-targeting period may be hampering the identification of this coefficient, as we explain in the next subsection. The rest of estimates of the conditional variance are rather similar to those obtained with the baseline Q-STARCH model, as the conditional variance equations are also equal to (2).

Finally, Table 5 also reports likelihood ratio tests (LRT) of the null of $H_0 : \lambda_L = 0$ versus the alternative that this parameter is different from zero, as a test of improvement of the model fit after the introduction of the LS intervention. The LRT is significant at 5 percent for Chile, Colombia and Peru. Note that, the LRT of Peru is particularly significant, which implies a better fit of the model after introducing the intervention, despite the lack of significance of $\hat{\lambda}_L$. This positive outcome in favor of IT mechanisms in highly dollarized economies like Peru is against the results of Morón and Winkelried (2005). This result indicates that, in some cases, nonlinearities present in inflation data might be masking the reduction in inflation level associated with IT.

4.2 Measuring the effects of IT on inflation volatility

The empirical evidence suggest that the omission of regime changes in the conditional variance equation specification of a GARCH type model may lead to overestimate significatively the degree of persistence than actually exists; see, for instance, Lastrapes (1989). This fact has important implications in terms of understanding the effects of a specific monetary policy, like the implementation of a formal IT mechanism.

Our empirical strategy is also to introduce dummy variables in the conditional variance of the chosen Q-STARCH specification, once we have identified the dates of structural breaks in inflation volatility. This exercise is related with the work by Aggarwal et al. (1999) on emerging stock markets, but we use a different baseline model and maintain the specification of the LS outliers in the measurement equation, as in previous subsection. The dummy variables of the conditional variance are going to account for the effects of possible regime shifts on volatility. Its introduction in the model is relevant, not only for policy-makers to interpret more precisely the impact of IT in variance dynamics, but also from the technical point of view, as, theoretically, volatility persistence is overestimated when standard GARCH models are applied to series with underlying changes in variance. Thus, ignoring those breaks in the conditional variance equation may cause a substantial overestimation of $\alpha_1 + \alpha_2$ (or $\gamma_1 + \gamma_2$, if the permanent component is heteroscedatic), as shocks to volatility are extremely persistent in GARCH models.

4.2.1 Testing for structural breaks in variance

To formally detect breaks in inflation variance, we apply the iterated cumulated sum of squares (ICSS) procedure introduced by Inclán and Tiao (1994) (henceforth $I\&T$) to the residuals of the estimates of model (1) with homoscedastic disturbances, $\widehat{\nu}_t$. This kind of tests has been broadly used in empirical applications to detect break points in variance (see Aggarwal et al., 1999, or Ewing and Malik, 2005). The $I\&T$ test statistic is given by

$$I\&T = \sqrt{\frac{T}{2}} \max_k |D_k|, \tag{9}$$

where D_k follows

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T} \tag{10}$$

and $C_k = \sum_{j=1}^{k} r_t^2$ for $k = t = 1, ..., T$. The value of k that maximizes (9) is the estimated break date. As a preliminary analysis, Figure 3 represents $\sqrt{T/2}|D_k|$ for each country. If there is at least one sudden change in the variance, this magnitude will be greater than the critical value.[11] The test identifies significant variance breaks in all countries but in Brazil, where no break is detected. For the rest of the countries the pattern is relatively similar, regardless of the adoption of IT.

Nevertheless, $I\&T$ test is not adequate to detect multiple breaks, as they may be masked. To overcome this problem, Inclán and Tiao (1994) proposed an iterative algorithm based on successive applications of $I\&T$ test to pieces of the series, splitting them consecutively after finding a structural break. Moreover, Andreou and Ghysels (2002) demonstrate that $I\&T$ test suffers from size distortions that tend to increase with the sample size when the variance process is dependent. To avoid both caveats of the test, we use a nonparametric adjustment based on the Barlett kernel, as recently applied by Rapach and Strauss (2008).[12]

Once we apply the ICSS procedure to the residuals of inflation series of the IT countries, we do not identify any break in the inflation variance of Brazil, whereas we detect one break

[11] Under variance homogeneity, the critical value of ± 1.36 is the 95th percentile of the asymptotic distribution of $max_k \sqrt{T/2}|D_k|$.

[12] We calculate the modified ICSS algorithm using the GAUSS procedures available from Andreu Sansó web page http://www.uib.es/depart/deaweb/personal/profesores/personalpages/andreusanso/we. We thank David Rapach for providing the modification of the code appropriate for sample sizes up to 7000 observations.

in the series of Chile (October 1993), Colombia (April 1999) and Peru (February 1995); and two breaks in Mexico (March 1983 and August 1988). It is important to note that in the case of Chile, Colombia and Peru, these breaks are approximately around the date of adoption of the IT regime. The case of Brazil is particularly relevant, as the estimates indicate that the introduction of IT is not associated neither with a decrease in the inflation level nor in the volatility, although IT has been successful in reducing long-run volatility persistence. This outcome is a result of including the period between 2001 and 2002 in the sample, when exchange rate depreciations occurred. This period was a stress test for the IT framework in Brazil, as noted by Minella *et al.* (2003). Even with this shock in Brazilian inflation, estimates in Table 4 show that IT helped to avoid a more persistent inflation uncertainty.

4.2.2 Model estimation

Once we have identified the breaks in the inflation volatility of the five inflation targeting countries, we introduce these breaks in the corresponding conditional variance equation. The main objective is to analyze the implications of the adoption of an IT regime in terms of volatility reduction. We focus on the study of the direct effect of a LS outlier on the intercept of the conditional variance equation.[13]

This generalization of the Q-STARCH model is relatively straightforward, and it consists on considering model (5) with disturbances following these expressions

$$\begin{aligned} h_t &= \alpha_0 + \lambda_V^h w_t + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 \varepsilon_{t-1} \\ q_t &= \gamma_0 + \lambda_V^q w_t + \gamma_1 \eta_{t-1}^2 + \gamma_2 q_{t-1} + \gamma_3 \eta_{t-1}, \end{aligned} \tag{11}$$

where w_t is a LS outlier defined by (6), and λ_V^h and λ_V^q are their coefficients in the short and long-run conditional variance disturbance processes, respectively. The intercept of the conditional variance of each component is different before and after the break, where it is $\alpha_0 + \lambda_V^h$ and $\gamma_0 + \lambda_V^q$ for the short-run and long-run innovations, respectively. This specification can be also generalized for the case of more than one break in the volatility equation, as in Mexico.

[13]We have also analyzed interventions in the asymmetry parameter, α_3 or γ_3. The interpretation of these results did not change significatively with respect to the proposed additive dummy and they are available upon request.

Before estimation, we reparameterize the conditional variances of the unobserved innovations to guarantee the positivity of h_t and q_t, as proposed by Sentana (1995) for the QGARCH(1,1) case, in the following way

$$
\begin{aligned}
h_t &= a_0 + \lambda_V^h w_t + a_1^2(\varepsilon_{t-1} - a_3)^2 + a_2^2 h_{t-1} \\
q_t &= g_0 + \lambda_V^q w_t + g_1^2(\eta_{t-1} - g_3)^2 + g_2^2 q_{t-1}
\end{aligned} \tag{12}
$$

where $\alpha_0 = a_0 + a_1^2 a_3^2$, $\alpha_1 = a_1^2$, $\alpha_2 = a_2^2$ and $\alpha_3 = -2a_3a_1^2$. Note that $\alpha_0 = a_0 + \lambda_V + a_1^2 a_3^2$ after one break in volatility. Similar conditions apply to the parameters of q_t. Then, the QML estimator can be calculated after minor changes in the expressions of the conditional variances of the disturbances, H_t and Q_t, of the Kalman filter, where the terms $\lambda_V^h w_t$ and $\lambda_V^q w_t$ should be added, respectively. After running the filter, the Gaussian likelihood is computed as in (4).

Note that, as stated in Baillie and Bollerslev (1989), the LS intervention represented in expression (11) is not a proper level shift but, due to the QGARCH parametrization of conditional variances, a gradual shift to a new level of unconditional variance. Indeed, in period t_{IT} the immediate effect of the LS outlier on h_t and q_t is λ_V^h and λ_V^q, respectively. Nevertheless, in t_{IT+1} the effect in the previous period will lead to an increase in h_{t+1} and q_{t+1} of $(\alpha_1 + \alpha_2)\lambda_V^h$ or $(\gamma_1 + \gamma_2)\lambda_V^q$. To offset this effect, an alterative specification of the conditional variances in (11) should contain the terms $-(\alpha_1 + \alpha_2)\lambda_V^h w_{t-1}$ or $-(\gamma_1 + \gamma_2)\lambda_V^q w_{t-1}$. For the sake of robustness, both specifications of the conditional variances have been fitted, although differences of the estimates are almost negligible. The specification finally chosen is the one that maximizes the likelihood.

Table 5 also shows the estimates of the Q-STARCH model with interventions in both the level and variance of inflation. Estimates of this model are denoted as LO+VO (Level Outlier and Volatility Outlier) and are quite similar to those reported in Table 5 for the Q-STARCH specification with LO interventions. After controlling for possible breaks in variance, persistence of inflation volatility is lower only in Peru, which is the only case consistent with Lamoureux and Lastrapes (1990). That is, according to these estimates, the adoption of a formal IT regime has reduced long-run uncertainty persistence in Peru. Nevertheless, and contrary to the results reported in Table 4 for the pre-targeting and after-targeting subsamples, there is not a strong evidence of volatility persistence decrease after controlling for volatility breaks in the remaining countries. Even in Colombia, volatility persistence increases due to the specification change of the heteroscedastic component. Note that in the LO+VO model estimates of Peru, $\widehat{\lambda}_L$ becomes negative and significant, contrary to the estimates of the LO model.

Table 5 also reports the LRT statistics for the null of $H_0 : \lambda_V = 0$ against the alternative that this parameter is different from zero. We find strong evidence of structural change in the variance of Chile, Mexico and Peru, whereas we cannot reject the null in the case of Colombia. Finally, we also test for the joint null of $H_0 : \lambda_L = \lambda_V = 0$, where results are similar to previous test. That is, although the evidence in favor of the reduction in volatility persistence is conclusive just for the case of Peru, this latter test confirms a better fit of the model with interventions in the variance equations.

5 Conclusions

This paper analyzes inflation dynamics in eight Latin American countries, both targeting and non-targeting, to disentangle possible benefits associated with IT in terms of lower level, volatility and volatility persistence. The chosen model for the empirical application is the Q-STARCH model with interventions, as it is rather parsimonious and nests certain empirical characteristics of inflation series. Moreover, the model accounts for conditional heteroscedasticity of inflation and it can distinguish between the dynamics in the long-run and in the short-run. Besides, as the conditional variance specification is an asymmetric GARCH model, the fulfillment of the Friedman hypothesis can be tested. Finally, the introduction of interventions in the model, both in the level and volatility of inflation, allows to control for the impact of IT on inflation and inflation volatility dynamics.

In general, the outcomes support the view that IT has associated gains in terms of lower inflation level and uncertainty, which suggest an independent role for formal targets. In this sense, IT adoption has implied additional benefits for macroeconomic stability in these countries, apart from the gains related to the global inflation moderation of the last years. The estimations indicate the following results: (i) The model identifies a lower inflation level and volatility after IT adoption in Chile, Colombia, Mexico and Peru, whereas the results may not be so conclusive for Brazil. Nevertheless, we identify a reduction in volatility persistence of the Brazilian inflation after IT adoption. (ii) The Friedman hypothesis fulfills in all inflation targeting countries, whereas Argentina is the unique non-targeting country of the sample where this effect holds. This fact implies that the inflation decrease may have contributed to consolidate lower levels of volatility in some of the IT countries, perhaps reflecting gains of credibility associated to IT. (iii) The long-run component of all inflation series, except for the Colombian inflation, is conditionally heteroscedastic. This means that, in most of the cases, these benefits associated with IT will have an effect on the long-run inflation uncertainty. (iv) The introduction of formal IT mechanisms has an impact on the degree to which shocks to volatility persist over time. IT adoption has reduced the persistence of inflation uncertainty in all countries but in Colombia, where evidence is not conclusive. In general, the estimated volatility persistence is bigger in the three non inflation targeting countries. Nevertheless, this evidence on volatility persistence is in conflict with the estimates of the model with LS interventions in variance, although the fit of the model is improved.

These results have important policy implications for this set of Latin American countries, as IT adoption is associated with lower inflation and inflation volatility. Nevertheless, these conclusions need to be further qualified. First, as our paper does not cover causality issues, IT might be associated with lower inflation level and volatility, but this not implies that IT causes this better performance. Second, this paper does not deal with the issue of inflation expectations, which is another limitation of the paper. The effect of IT on inflation expectations is also controversial in the empirical literature, but it is out of our scope. Finally, from the technical point of view, innovations of the model still exhibit excess kurtosis even after introducing conditional heteroscedasticity and additive innovations, which implies that there is still room for model improvement.

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Figure 1: Inflation series for eight Latin American countries and dates of IT adoption. Sample period since 1995.

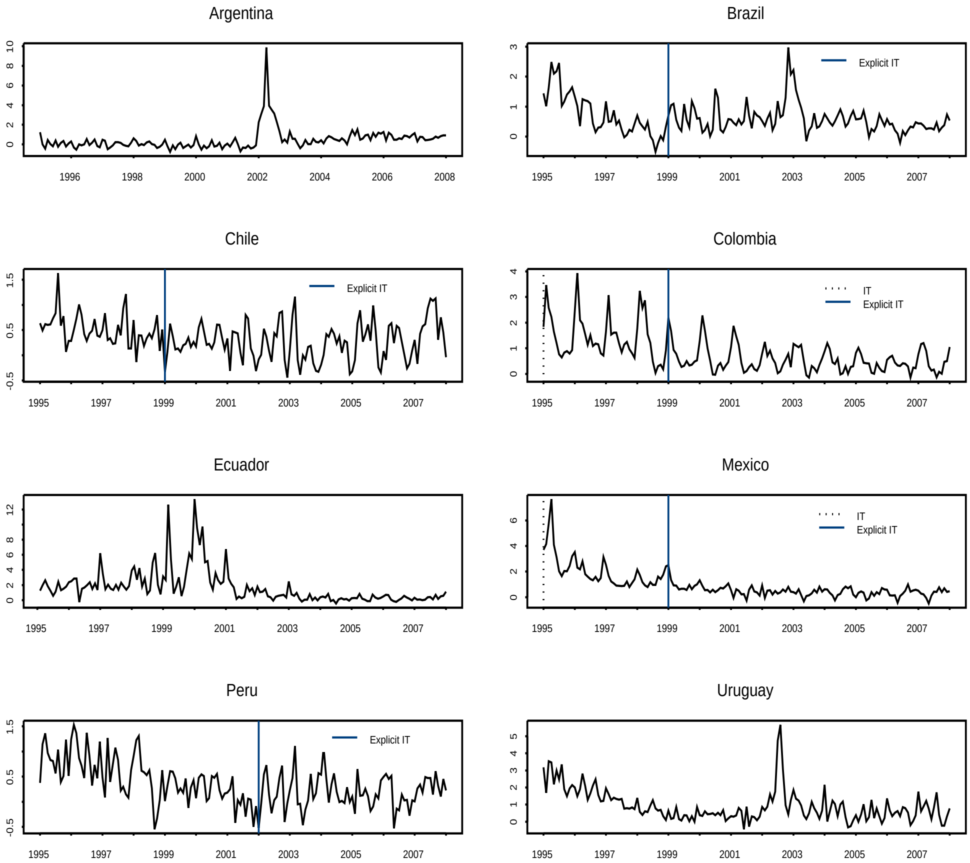

Table 1: Summary of inflation targeting countries and dates of IT adoption in Latin America.

Country	Date adoption IT	Date adoption explicit IT	Current inflation target
Brazil	06/1999	06/1999	4.5% (±2%)
Chile	09/1990	09/1999	3%
Colombia	1995	09/1999	4% (±0.5%)
Mexico	1995	01/1999	3% (±1%)
Peru	02/1994	01/2002	2(±1%)

Source: IMF (2005), Vega and Winkelried (2005), Pétursson (2004) and national sources

Figure 2: Conditional volatilities of the heteroscedastic disturbance obtained after fitting baseline Q-STARCH model and dates of IT adoption.

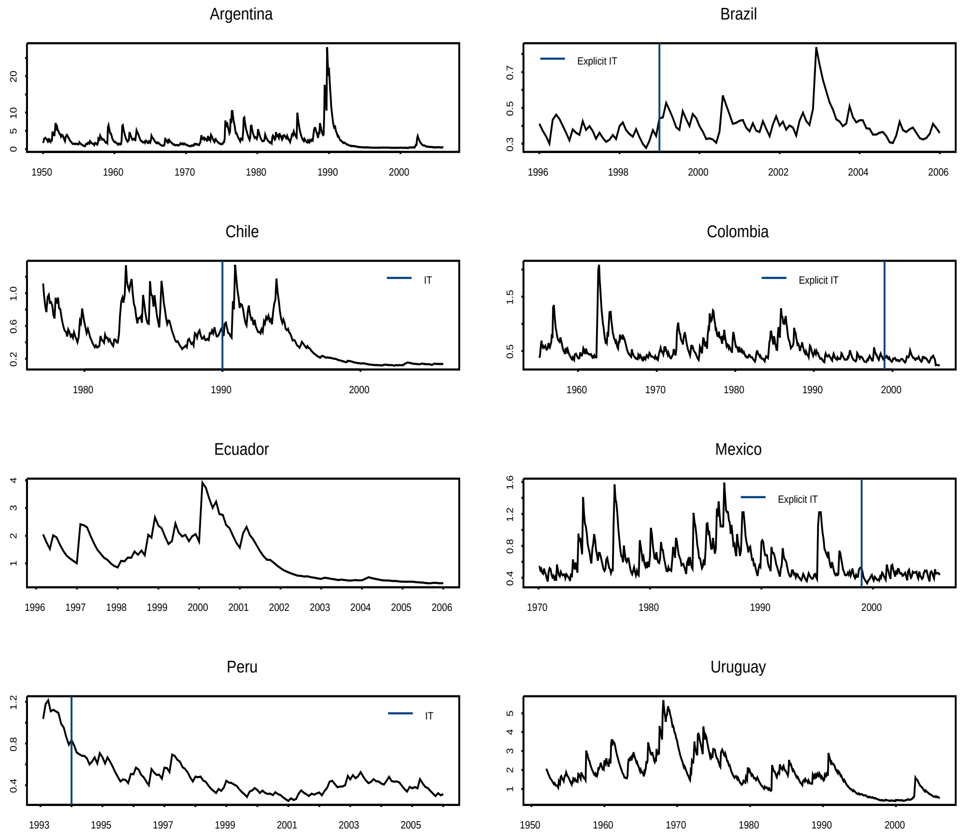

Figure 3: CUSUM plot for retrospective detection of variance changes -Inclán and Tiao (1994)- for eight Latin American countries.

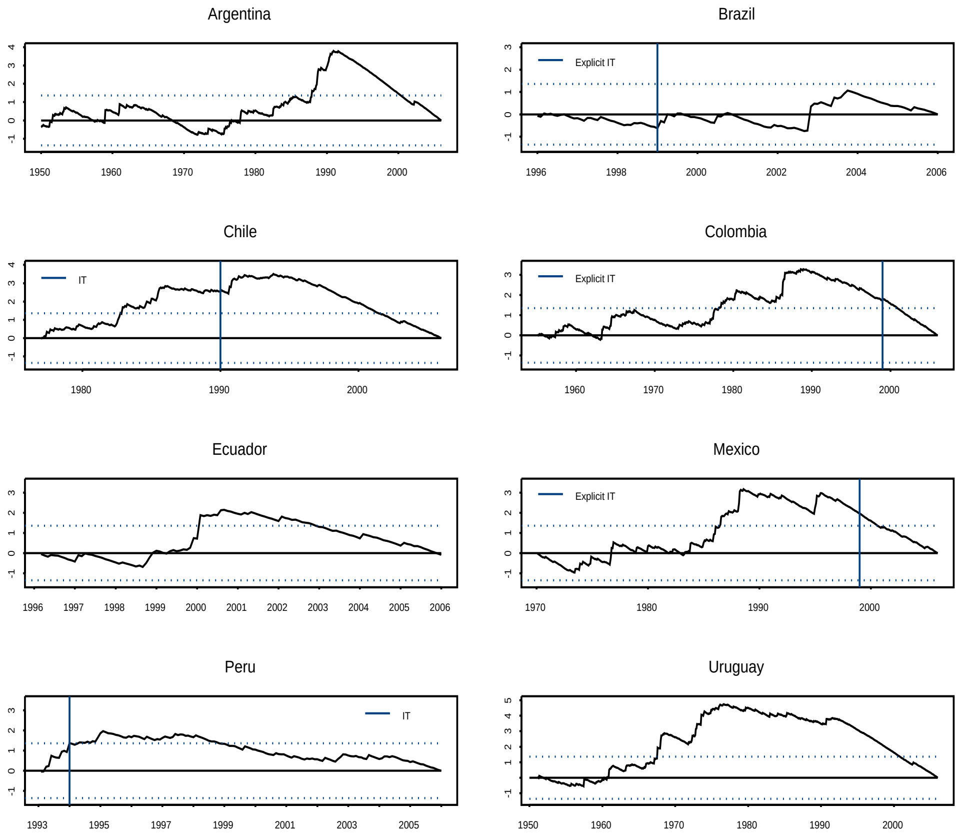

Table 2: Summary of descriptive statistics for the full sample of y_t and for the sample beginning in 1995:1.

	BRA		CHI		COL		MEX		PER		ARG		ECU	URU	
Sample period	1/1995 − 1/2006		1/1976 − 1/2006		2/1954 − 1/2006		2/1969 − 1/2006		2/1992 − 1/2006		2/1943 − 1/2006		2/1995 − 1/2006	2/1950 − 1/2006	
Sample size (T)	133		361		624		444		168		756		132	672	
	Full sample		Full sample	Since 1995:1	Full sample	Since 1995:1	Full sample	Since 1995:1	Full sample	Since 1995:1	Full sample	Since 1995:1	Full sample	Full sample	Since 1995:1
Mean	0.6993		1.4081	0.3306	1.2165	0.8825	1.8634	1.0365	0.8128	0.3727	4.0263	0.4150	1.9390	2.6700	1.0157
SD	0.6301		1.7925	0.3656	0.9955	0.7868	1.8800	1.0279	1.1144	0.4454	6.8088	1.1713	2.3399	2.6331	0.9984
	Pre-Target	After-Target	Pre-Target	After-Target	Pre-Target	After-Target	Pre-Target	After-Target	Pre-Target	After-Target					
Mean	0.7289	0.6792	2.3044	0.5570	1.3126	0.5340	2.1852	0.5043	3.1037	0.4310					
SD	0.6968	0.5839	2.1367	0.6891	1.0118	0.4799	1.9477	0.3997	1.0340	0.5008					

SD: Standard Deviation.

Table 3: Summary of descriptive statistics of the stationary transformation $\Delta_{12} y_t$.

	BRA		CHI		COL		MEX		PER		ARG		ECU	URU	
	Full sample		Full sample	Since 1995:1	Full sample	Since 1995:1	Full sample	Since 1995:1	Full sample	Since 1995:1	Full sample	Since 1995:1	Full sample	Full sample	Since 1995:1
Mean	−0.1264		−0.2795	−0.4303	0.0086	0.0415	−0.0027	−0.0222	−0.2708	−0.0934	0.0199	0.4154	−0.1390	0.0039	−0.2420
SD	0.7773		1.3206	1.6278	0.9107	0.9965	1.5642	1.1005	0.7087	0.4868	6.8230	1.1716	2.5626	2.9951	1.1087
SK	−0.2590		−1.6744*	−1.1787*	0.3247*	0.2626	−1.0327*	1.7055*	−0.9932*	−0.0097	−0.9599	4.7541*	0.6653*	−0.2435*	0.9849*
κ	4.2406*		11.2551*	7.3674*	4.6599*	4.0099*	8.5749*	9.6263*	4.9092*	3.4448*	21.5381*	34.7619*	7.4377*	7.1329*	12.8404*
	Pre-Target	After-Target	Pre-Target	After-Target	Pre-Target	After-Target	Pre-Target	After-Target	Pre-Target	After-Target					
Mean	−0.3402	0.0044	−0.4600	−0.1026	0.0309	−0.1292	0.0345	−0.1553	−1.1470	−0.1978					
SD	0.6378	0.7704	1.7940	0.6451	0.9623	0.4602	1.7336	0.3806	1.0591	0.6231					
SK	0.2085	−0.5294*	−1.0936*	−0.7535*	0.2939*	−1.5794*	−1.0049*	−0.6915*	0.5690	−0.9701*					
κ	2.6394*	5.2143*	6.4319*	8.1118*	4.2304*	7.5142*	7.1637*	3.6989*	3.3627*	5.4680*					

* Significant at 5%; SD: Standard Deviation; SK: Skewness; κ: Kurtosis.

Table 4: Estimates of the Q-STARCH model with stochastic seasonality for inflation series. Sample period: Full-sample, pre-targeting and the after-targeting period.

	BRA			CHI			COL			MEX			PER		ARG	ECU	URU
	Full sample	Pre-target	After-target	Full sample	Pre-target	After-target	Full sample	Pre-target	After-target	Full sample	Pre-target	After-target	Full sample	After-target	Full sample	Full sample	Full sample
α_0	0.000001	0.000006	0.00001	0.0644	0.3211	0.1644	0.0136	0.0233	0.000000001	0.000000001	0.1017	0.0146	0.000000001	0.000000001	0.0233	0.0316	0.0084
	(0.00003)	(0.0001)	(0.00012)	(3.5167)	(4.3129)	(6.4905)	(1.5927)	(1.7889)	(0.0000001)	(0.0000001)	(2.8784)	(0.8265)	(0.00000004)	(0.0000001)	(1.3775)	(0.4258)	(1.0341)
α_1							0.2013	0.2018									0.1153
							(2.9276)	(2.6207)									(5.0716)
α_2							0.7411	0.7102									0.8833
							(9.8675)	(7.7759)									(38.8845)
α_3							0.1034	0.1372									0.0625
							(2.6642)	(2.8237)									(1.3647)
γ_0	0.0214	0.0089	0.0989	0.00007	0.0388	0.0007	0.0092	0.0114	0.0132	0.0307	0.0500	0.0042	0.0036	0.0081	0.0025	0.0035	0.0368
	(1.7159)	(0.2304)	(2.9844)	(0.3919)	(2.1745)	(0.1539)	(14.1513)	(9.4633)	(3.0749)	(5.8400)	(32.7593)	(2.3169)	(1.4073)	(1.1670)	(2.8048)	(0.6197)	(15.4635)
γ_1	0.0985	0.0701	0.1188	0.3054	0.5241	0.2374			0.4604	0.1951	0.0001	0.5466	0.1763	0.0851	0.5675	0.2704	
	(3.3378)	(0.9368)	(4.4778)	(31.1707)	(17.0489)	(1.6342)			(5.3054)	(35.3470)	(0.9350)	(5.9616)	(14.6544)	(3.1103)	(12.8350)	(7.6356)	
γ_2	0.7773	0.8803	0.3489	0.6944	0.2474	0.4044			0.5194	0.7364	0.9998	0.3628	0.8201	0.8653	0.4321	0.7292	
	(26.8777)	(8.8530)	(2.6996)	(70.0880)	(3.6867)	(2.5285)			(5.7274)	(134.2299)	(160.8124)	(2.7567)	(63.1995)	(16.8629)	(9.7780)	(20.4400)	
γ_3	0.0918	0.0500	0.2130	0.0095	0.2853	0.0264			0.1563	0.1549	0.4436	0.0938	0.0504	0.0526	0.0763	0.0241	
	(5.6238)	(0.6895)	(14.6737)	(1.5330)	(5.4384)	(0.2891)			(11.1672)	(12.4304)	(101.8235)	(3.4213)	(4.8645)	(7.1983)	(4.8450)	(1.0511)	
σ^2_ω	0.0003	0.0000002	0.0008	0.0022	0.000000001	0.0027	0.0118	0.0143	0.0011	0.0048	0.0066	0.0053	0.0009	0.0009	0.0054	0.0099	0.0002
	(0.7136)	(0.00001)	(0.6878)	(4.7607)	(0.000001)	(2.3783)	(12.6427)	(10.4698)	(0.9390)	(6.1243)	(5.1923)	(2.3896)	(1.4655)	(1.4077)	(4.1613)	(3.6838)	(1.5269)
$LogL$	−172.2154	−61.1239	−94.5466	−336.8955	−199.4804	−210.3688	−604.9177	−547.5237	−107.2699	−444.1343	−389.5223	−118.3735	−109.9746	−70.1997	−638.9264	−40.7690	92.1407
κ	3.462*	2.250*	5.588*	4.379*	3.622*	6.684*	6.493*	5.404*	2.629*	13.914*	3.469*	2.432*	4.246*	2.972*	11.3159*	5.385*	19.618*
$Q(1)$	0.546	0.285	1.183	0.036	0.557	6.1064*	65.210*	46.239*	2.483	1.471	275.87*	0.713	11.257*	9.950*	8.192*	8.951*	5.211
$Q(12)$	22.884*	11.173	11.425	33.734*	23.697*	52.512*	93.914*	69.322*	35.427*	28.788*	1852.0*	19.776	37.583*	34.869*	37.276*	16.526	31.243*
$Q^2(1)$	0.017	0.4520	0.144	3.315	0.783	2.960	2.414	1.499	0.163	0.109	188.68*	3.525	0.143	0.202	13.456*	1.248	11.186*
$Q^2(12)$	6.052	11.884	11.401	22.566*	9.8758	60.100*	8.544	11.809	6.335	2.808	1135.0*	28.717	8.525	5.198	142.08*	10.789	19.498

* Significant at 5%; κ: Kurtosis; $\rho(\tau)$: Correlation of order τ; $.Q(\tau), Q^2(\tau)$: Ljung-Box test statistic of order τ for the linear and squared residuals

Table 5: Estimates of the Q-STARCH model with stochastic seasonality for inflation series and one intervention in the level (LO) or in the level and volatility processes (LO+VO).

	BRA	CHI		COL		MEX		PER	
	LO	LO	LO+VO	LO	LO+VO	LO	LO+VO	LO	LO+VO
α_0	0.0003	0.0669	0.0650	0.0312	0.1353	0.0007	0.0169	0.0137	0.1101
	(0.0121)	(3.6035)	(3.9922)	(2.2237)	(5.8832)	(0.3588)	(0.7769)	(0.6771)	(5.2590)
α_1				0.2107					
				(3.3429)					
α_2				0.7114					
				(9.3390)					
α_3				0.1015					
				(2.5485)					
γ_0	0.0208	0.00007	0.0002	0.0064	0.0026	0.0307	0.0378	0.0022	0.0007
	(1.4233)	(0.3513)	(1.0305)	(11.1817)	(5.5657)	(5.9727)	(51.9603)	(1.0889)	(0.8426)
γ_1	0.1038	0.3146	0.3237		0.1883	0.2015	0.1724	0.2662	0.1233
	(3.4533)	(31.5091)	(14.1859)		(155.0339)	(35.8140)	(38.2598)	(6.9862)	(5.1288)
γ_2	0.7765	0.6852	0.6732		0.8017	0.7300	0.8123	0.7322	0.6736
	(18.8540)	(67.9412)	(47.3880)		(191.9121)	(127.6068)	(8.5422)	(18.7994)	(24.5925)
γ_3	0.0929	0.0095	0.0093		0.0914	0.1548	0.0232	0.0485	0.0182
	(5.2636)	(1.2774)	(0.8557)		(8.3338)	(12.4617)	(6.0872)	(3.6350)	(0.2072)
σ^2_ω	0.0003	0.0023	0.0023	0.0113	0.0111	0.0048	0.0111	0.0008	0.0008
	(0.6934)	(4.7808)	(5.2592)	(12.1763)	(10.9975)	(6.1524)	(7.8462)	(1.5961)	(1.4601)
λ_L	-0.0625	-1.4375	-1.4764	-0.0501	-0.0497	-0.1840	-0.1825	0.2071	-0.8032
	(0.3244)	(-14.8874)	(-7.2057)	(-12.0697)	(0.4134)	(1.9283)	(2.1610)	(0.8478)	(2.8244)
$log\ L$	-172.205	-334.919	-332.691	-602.856	-605.038	-444.014	-441.006	-105.932	-92.881
LRS, $H_0 : \lambda_L = 0$	0.0208	3.9330*		4.1220*		0.2406		8.0842*	
LRS, $H_0 : \lambda_V = 0$			4.4560*		-4.3636		6.0146*		26.1020*
LRS, $H_0 : \lambda_L = \lambda_V = 0$			8.3890*		-0.2416		6.2552*		34.1862*
κ	3.453*	4.338*	4.230*	6.458*	5.6705*	8.323*	8.2549*	3.839*	2.8453*
$Q(1)$	0.584	0.150	0.3382	65.634*	14.958*	0.062	0.0697	5.681*	7.1908
$Q(12)$	22.870*	32.810*	31.694*	93.451*	70.619*	41.174*	41.703*	30.546*	33.834*
$Q^2(1)$	0.015	3.378	2.2462	1.399	2.7983	0.0294	0.1626	0.002	7.1891*
$Q^2(12)$	6.212	19.292	17.624	8.856	8.4332	12.787	11.087	12.018	27.806*

*Significant at 5%; SK: Skewness; κ: Kurtosis; $\rho(\tau)$: Correlation of order τ; .$Q(\tau), Q^2(\tau)$: Ljung-Box statistic of order τ for the linear and squared residuals; LRS is $2(log\ L(u) - log\ L(r))$, where $log\ L(r)$ is the value of the log-likelihood under the restricted specification and $log\ L(u)$ under the unrestricted.