Elsevier Editorial System(tm) for Journal of Development Economics

Manuscript Draft

Manuscript Number:

Title: AN EMPIRICAL INVESTIGATION OF INFLATION TARGETING IN EMERGING ECONOMIES

Article Type: Full Length Article

Section/Category:

Keywords: Inflation Targeting, Emerging Economies, Intervention Analysis, Multivariate Structural Time Series Models

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Manuscript Region of Origin:

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# AN EMPIRICAL INVESTIGATION OF INFLATION TARGETING IN EMERGING ECONOMIES

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## Abstract**

This paper produces new empirical evidence regarding the 'new' monetary policy framework, known as Inflation Targeting. For this purpose, it applies intervention analysis to Structural Time Series models, in the case of a number of emerging economies. These results demonstrate that although Inflation Targeting has gone hand-in-hand with low inflation, the strategy was introduced well after inflation had begun its downward trend. There is the possibility, though, that the Inflation Targeting strategy 'locks in' low inflation rates. The evidence produced suggests that not only have emerging IT countries been successful on this score, but so have non-IT central banks.

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** The authors wish to thank Andrew Harvey from the Department of Economics, University of Cambridge, for his helpful comments and suggestions.

# AN EMPIRICAL INVESTIGATION OF INFLATION TARGETING IN EMERGING ECONOMIES

## 1. Introduction

Inflation targeting (IT) is a new way of conducting and implementing monetary policy, within the confines of what has come to be known as the 'New' Consensus in Macroeconomics (see, for example, Arestis and Sawyer, 2004). IMF (2005) reports that 21 countries have adopted IT, and the number is expected to increase (see, also, Sterne, 2002). 8 out of the 21 countries are developed economies, and we have assessed the performance of this policy in the case of developed countries in a recent paper (Angeriz and Arestis, 2005). The purpose of the current paper is to assess the performance of the 13 emerging countries.[1] We have also added to the list Poland, a country that introduced IT in January 1999, so that the total number of countries in our sample of IT emerging-country cases is 14. IMF (2005) notes that while IT in developed countries has been the focus of many studies, "there has been little analysis of the effects of inflation targeting in emerging market countries" (p. 161). This paper contributes to the debate by utilizing a new technique for this purpose, known as Structural Time Series and Intervention Analysis model (see, for example, Harvey and Durbin, 1989, Harvey, 1996). This

[1] There is another form of IT adopted by a number of emerging countries. This is termed as 'inflation targeting lite', which may be defined as that regime where central banks "announce a broad inflation objective but owing to their relative low credibility they are not able to maintain inflation as the foremost policy objective. Their relatively low credibility reflects their vulnerability to large economic shocks and financial instability and a weak institutional framework" (Stone, 2003, p. 8). We do not deal with this group of countries in this paper.

technique can deal with the effects of IT implementation and also with the possibility of ‘locking-in’ inflation rates to low levels and within the confines set by the IT strategy.

We begin in section 2 by elaborating on the methodology we have adopted, and highlighting the main ingredients of the Structural Time Series and Intervention Analysis model. We explain the more technical aspects of this model in an attempt to assess IT in section 3. The empirical evidence we have amassed is reported and discussed in section 4. Finally, section 5 summarizes and concludes.

## 2. Methodology

In time series analysis predicting with a deterministic global trend, i.e. performing forecasts or estimating unobserved components (signal extraction) with a fixed slope, may result in significant errors, especially when the trend changes its shape through time. We may demonstrate the problem by referring to equation (1) below:

$$y_t = \alpha + \beta \cdot t + \varepsilon_t \tag{1}$$

with t = 1 ,..., T, and where α and β are parameters and $\varepsilon_t$ is a random process with a zero mean and variance $\sigma^2$. This deterministic linear trend plus noise model could adjust relatively well by, for instance, letting the disturbance term to follow a general stationary autoregressive-moving-average (ARMA) process, in which case predictions based on (1) would have to account for serial correlation. However, by incorporating a global trend and constant parameters, the model assumes that all data points are scattered around a trend that does not change. This assumption may not be appropriate in that the parameters might not be necessarily constant throughout.

Allowing the parameters to vary with changes in the data is a more satisfactory procedure. By doing so, the trend would only be ‘locally’ fixed and it is the most recent trend to the end of the sample that should be extrapolated in order to prevent systematic errors. In other words, local trends should be used instead of global ones. Several methodologies help to handle this problem by putting more weight on the most recent observations. One such procedure is the Holt-Winter (Harvey, 1993, p.111), a recursive approach, and one through which changes in level and slope are computed by allocating lesser weights to past observations in an ad-hoc fashion. Box and Jenkins (1975) suggest a second approach, the autoregressive-integrated-moving-average models (ARIMA), which has become the standard time-series methodology since then. As a first step, this method operates by differencing a non-stationary time series until it displays attributes characteristic of stationary ones. Then, the appropriate autoregressive-moving-average model (ARMA) is applied to capture the serial correlation in the resulting series.

A more promising way forward, and one that fits a great deal more with the issue in hand, is the adoption of the Structural Time Series models (STMs) approach (see, for example, Harvey, 1996). This methodology provides a very different rationale for local linear trend forecasting by allowing the parameters in equation (1) to evolve according to a stochastic process. It is important to note that not only local trends are estimated. By modeling the most protruding features of a series, STM methods decompose time series into unobserved components with specific and meaningful dynamic properties. In this respect, trends are examples of the components that are the subject of modeling, but also these models examine seasonal components, cycles and short-term shocks closely as stochastic components, following generally a random walk. It is worth noting that these components may be treated as a deterministic function of time, as in the case of the deterministic linear trend plus noise model presented in equation (1), if the corresponding variances are estimated as null (see Koopman *et al*, 1995). This is a better way of handling the problem in hand, since STMs offer different characteristic patterns, whose dynamics may be analyzed and, in the case of multivariate STMs, even compared across the countries included in the model. By contrast, in the ARIMA approach trends and seasonals are removed from the series before any application of the ARMA modelling is performed. An added advantage of the structural approach is that STMs may also benefit from prior knowledge of the main patterns of dynamic characteristics of the series in consideration, which enables the investigator to produce more parsimonious models.

Indeed, the approach of decomposing a series in distinctive ‘unobserved components’ constitutes an attractive methodology for isolating permanent and transitory changes (for instance, trend and seasonal effects) from those happening due to events identified a priori by the researcher; in our case this is precisely the implementation of IT. In this framework, the effects of such monetary strategy are assessed by bringing a new component into the model, which consists of a variable characterizing the intervention (generally a dummy variable), multiplied by a coefficient that measures the impact. This kind of analysis of the effects of such events is known in the literature of time series as intervention analysis ever since Box-Tiao (1975).

One of the main problems in studying the impact of IT relates to the so-called ‘fundamental problem of causal inference’ (Holland, 1986). This is a common problem in many disciplines, and in Economics in particular. In attempting to identify causality effects it should be necessary to assess the difference between the results that a unit produces after it has been subjected to intervention from those that would be obtained if the unit were not subjected to intervention. Obviously the latter type of evidence is not available, hence several strategies have been recommended to deal with this statistical problem. Classic univariate STMs, implicitly predict a counterfactual by adding up all estimated components for the series being studied, except for the one corresponding to intervention (see, for instance, Harvey and Durbin, 1986). In order to perform this decomposition the dynamic patterns of the different components are explicitly modelled, thereby facilitating the identification of the changes in the trend in comparison with a situation where the change would not have occurred. Harvey (1996) suggests that incorporating in the model units not subjected to intervention, thereby using them as ‘control groups’, would contribute to this purpose. This recommendation highlights a further advantage in utilizing STMs. This is that it constitutes an ideal framework for conducting an assessment of IT effects with a control group, that is a group of countries that do not pursue the IT strategy, for two reasons. The first is due to the dynamic characteristics of different components, which may be compared across countries. The second reason is that since multivariate STMs take into account information embedded in the correlation between the unobserved components, they deliver a more efficient estimation for the intervention effect and a more satisfactory decomposition of the unobserved components. In this paper, we include, when suitable, the IT countries that are subject to intervention, and the non-IT countries that comprise our ‘control group’. When the available data set is incomplete, however, simpler STMs are utilized.

We turn our attention next to the multivariate Structural Time Series models with Intervention Analysis.

## 3. Structural Time Series Models and Intervention Analysis

### 3.1 Univariate Structural Time Series Models

Following Harvey (1996) and Angeriz and Arestis (2005), we begin with the Local Linear Trend version of the STM, appropriately generalized to account for intervention analysis, for the purposes of assessing the effects of IT. We start by describing the univariate STM framework, followed by the multivariate case. The univariate model consists of the following set of equations.

$$\pi_t = \mu_t + \gamma_t + \delta \cdot \omega_t + \varepsilon_t \tag{2}$$

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{3}$$

$$\beta_t = \beta_{t-1} + \zeta_t \tag{4}$$

where $\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$, $\eta_t \sim NID(0, \sigma_\eta^2)$, $\zeta_t \sim NID(0, \sigma_\zeta^2)$,

$$\gamma_t = \sum_{j=1}^{2} \gamma_{j,t}; \quad \begin{bmatrix} \gamma_{j,t} \\ \gamma_{j,t}^* \end{bmatrix} = \begin{bmatrix} \cos\lambda_j & \sin\lambda_j \\ -\sin\lambda_j & \cos\lambda_j \end{bmatrix} \cdot \begin{bmatrix} \gamma_{j,t-1} \\ \gamma_{j,t-1}^* \end{bmatrix} + \begin{bmatrix} \kappa_{j,t} \\ \kappa_{j,t}^* \end{bmatrix}; \quad \begin{matrix} j = 1,2 \\ t = 1,\dots,T, \end{matrix}$$

$\kappa_t \sim NID(0, \sigma_\kappa^2)$, $\kappa_t^* \sim NID(0, \sigma_\kappa^2)$, *and* $E(\kappa_t \kappa_t^*) = 0.$

Furthermore, $\pi_t$ represents inflation levels for the emerging IT economy in time period t, and this is the series to be explained. According to the model a number of 'unobserved stochastic components', namely $\mu_t$, $\gamma_t$, $\delta \cdot \omega_t$, $\varepsilon_t$, $\beta_t$, $\eta_t$, $\zeta_t$, $\kappa_t$, contribute to explaining the dynamic patterns of inflation. $\mu_t$ is a stochastic trend (usually also labeled as the 'underlying level'), and receives random shocks both directly in its level (through $\eta_t$, the perturbation driving the underlying level) and through its stochastic slope $(\beta_t)$, as shown in the *level equation* (3). The *local equation* (4) assumes that $(\beta_t)$ follows a random walk. $\gamma_t$, in the *measurement equation* (2) represents the current state of the stochastic seasonal cycle. A trigonometric form is chosen to account for this component. To do so, the frequency in radians is defined as $\lambda_j = \pi \cdot j/2$, while $\gamma_t^*$ is needed by construction for the purpose of defining $\gamma_t$, and has no intrinsic importance. $\omega_t$ is the intervention variable, δ registers the intervention's impact on inflation, and $\varepsilon_t$ are perturbations (labeled in the tables below as 'irregulars') with a direct impact on the series. $\zeta_t$ are the errors corresponding to slopes and, finally, $\kappa_t, \kappa_t^*$ are mutually uncorrelated seasonal perturbations, with $\kappa_t^*$ included by construction as just as in the case of $\gamma_t^*$, that is for the sole purpose of defining $\kappa_t$.

### 3.2 Multivariate Structural Time Series Models

Multivariate STMs constitute a natural generalization of these models. The elements described in the univariate model are now vectors, which include the different series, and these, in turn, are decomposed in vectors of unobserved components (see Harvey, 1989, for a brief description of these models). In multivariate STMs random perturbations, labeled as $\varepsilon_t$, $\eta_t$, $\zeta_t$, $\kappa_t$, are multivariate vectors representing the different series that are being modeled. These vectors are distributed NID with zero means and with $\Sigma_\varepsilon$, $\Sigma_\eta$, $\Sigma_\zeta$, $\Sigma_\kappa$ being the corresponding disturbance matrices.[2] Note that non-diagonal elements in the latter provide useful information about correlations between unobserved

[2] Assumptions made about the covariance matrix of ( $\kappa, \kappa$ ) and ( $\kappa^*, \kappa^*$ ) are usually imposed for reasons of parsimony and, also, for the model to be identifiable.

components across countries.[3] This category of models are referred to as Seemingly Unrelated Time Series Equations (SUTSE) models, in view of their similarity with Zellner's (1963) Seemingly Unrelated Equations (SURE) models. Just like SURE, these models exploit the information embedded in the correlation of perturbations, thereby enabling in the process the achievement of more efficient estimates for the parameters that are related to the intervention variable (Harvey, 1989, p. 451). Efficiency gains are obtained when SUTSE models are employed. Harvey (1996) demonstrates this proposition in the case of the bivariate model with fixed trends, considering one of the series as a control group. Harvey (op. cit.) compares the variance of the coefficient corresponding to the intervention estimated by means of SUTSE models with the variance obtained for the coefficient estimated with the univariate model. It is shown that the variance estimated with SUTSE is lower than that obtained when the univariate model is employed (see, also, Angeriz and Arestis, 2005).

### 3.3 Intervention Analysis

The intervention variable $\omega_t$ should be defined to suit the problem in hand, since in modeling it may assume different forms. In this paper, we basically test the null of the absence of a shift in the underlying level of the series, after the adoption of IT, at time t = τ. In order to account for a change in the trend, we postulate $\omega_t$ as a step variable. This takes the value of 0 for all periods prior to the point of intervention at time τ, and 1 thereafter. So that we assign 0 to all periods from t = 1 to t = τ-1, and 1 from t = τ

[3] Note that the deterministic linear trend plus noise model results as a specific case of the more general linear trend model when $\Sigma_\varepsilon = \Sigma_\eta = 0$. We then have: $\mu_t = \mu_{t-1} + \beta$ , which is a linear trend.

onwards. The same type of effect results from defining a pulse variable in the level equation, i.e equation (2). Pulse variables are defined as null except for the period when the intervention starts, when it takes the value of 1. It is also possible to define other forms of intervention,[4] but this approach is particularly pertinent in view of the fact that all the countries in our sample that adopted IT have not abandoned it over the period of experimentation. The key characteristic of this method, therefore, is that the dynamics following an intervention have to be defined by the investigator, based on prior knowledge, and then submit them to diagnostic testing (Harvey and Durbin, 1986; Harvey, 1996).

The statistical application of Structural Time Series Models and Intervention Analysis is performed by defining it in a state space form. The Kalman filter is, then, used to estimate the different components of the series as a recursive method for calculating the optimal estimator, given all the information available up to the point of the estimation. Signal extraction (smoothing) is used to estimate the unobserved components, accounting for all the information available in the sample.

In what follows we apply the statistical application of Multivariate Structural Time Series Models and Intervention Analysis, as discussed in this section. The application of this framework embraces the emerging countries that have adopted the IT strategy along with other control group countries as further explained immediately below.

## 4. Empirical Evidence

[4] We discuss these different forms of intervention in Angeriz and Arestis (2005), including the form used for the purposes of studying IT, and there too we conclude that a step variable is most appropriate.

### 4.1 Prolegomena

In 1991, the Central Bank of Chile introduced and implemented the IT strategy. It was the first of a number of emerging countries, which adopted and implemented the IT strategy in the 1990s. Indeed, Brazil, Chile, Colombia, Iceland, Israel, Mexico, Peru, Philippines, South Africa, South Korea and Thailand followed this lead with real enthusiasm that such policy would tame inflation and contain inflationary expectations. IT is, of course, an important operational framework for 'new' monetary policy that aims at price stability.[5] The evidence so far on the experience of these countries with IT has not been as numerous and varied as in the case of the developed countries (Angeriz and Arestis, 2005). Such evidence as there is suggests that IT is a success story in emerging countries. It is associated with a statistically significant larger reduction in the level and standard deviation of inflation as compared to other regimes. It also leads to a reduction in the level and volatility of inflation expectations. This body of evidence, though, is lacking in counterfactuals (IMF, 2005), a weakness that we address by employing STMs.

We assess in this paper the effects of IT by applying multivariate STMs, one for each IT country for those countries for which the complete span of data is available, that is,

[5] IT may be contrasted with alternative strategies, such as money supply or exchange rate targeting, a number of emerging countries have actually pursued (and are actually pursuing currently; see, for example, IMF, 2005). The main difference is that unlike IT, which targets inflation directly, the alternative strategies seek to achieve price stability through intermediate variables, such as growth of the money supply or the exchange rate of an 'anchor' currency. IT is normally conducted over some horizon, in which case inflation forecasts become important. Under these circumstances inflation forecasts become the *de facto* intermediate target for policy. It is for this reason that IT refers to sometimes as 'inflation forecast targeting' (Svensson, 1998).

1980(Q1)-2004(Q4). In these cases, models are composed by each country that implements the IT strategy and two countries, the European Union (EU) and the United States (US), two cases that do not pursue IT, which comprise the control group. $\pi_t$ is, therefore, considered as a vector of 3x1, composed of the inflation prevailing at time t in the corresponding IT country and also the inflation at time t in the two non-IT cases used as the control group. Inflation is defined as the headline CPI. As mentioned above, we start by applying the most general Local Linear Trend model. When goodness of fit measures are very low, we remove those components, such as seasonals and slopes, which are estimated as non-random by the model. This occurs with the cases of Philippines and Iceland, but it is important to note that the results regarding the estimations of the intervention effects in these countries, after simplifying the model specification, do not contradict the evidence collected with the more general models.

Most of the countries in our sample afford data for the period 1980(Q1) to 2004(Q4). However, there are exceptions in the cases of Brazil, Israel, Mexico, Peru and Poland. These countries have experienced hyperinflation periods, which cannot be handled properly by the models utilized. In these cases the periods selected for estimation span from immediately after the hyperinflation processes abated until 2004(Q4). Models estimated for the Czech Republic and Poland are also estimated with a shorter span because data are only available after 1991 for these countries. In all these cases univariate STMs were computed. This is required in order to economize on the estimated parameters. Precise dates that cover the periods of estimation in the case of these countries are provided at the foot of Table 1. All estimations were run using STAMP as in Koopman et al. (1995).

**4.2 Empirical Evidence: Time Trend and Seasonality**

We begin by applying the more general Local Linear Trend Model, as described above, allowing for the presence of a slope in all trends. We add to this model a seasonal component, supported by visual inspection of the evidence as presented in Figure 1, and by regression analysis, the results of which are reported in Table 1 below.

Figure 1 shows quarterly data of inflation levels for the case of the fourteen IT and the two non-IT countries, EU and the US. The period of estimation is 1980(Q1) to 2004(Q4) for all countries; there are, however, exceptions as noted above and in the notes at the foot of Table 1. The seasonal pattern in most of the countries is apparent. Further insights are obtained by regressing inflation in differences simply against dummies representing the effects of each quarter, which purport to register seasonality effects. We label these variables as Qj, with j=1 ….. 4, being Qj = 1 if the time period of the observation corresponds to quarter j and 0 otherwise. We only consider Q2 to Q4 to avoid perfect multi-colinearity. The results of this exercise for all countries are presented in Table 1. In addition to the t-statistic, we employ two statistics designed to assess the goodness of fit of these models, the $R^2$ and the F-test. They confirm the impression gauged by the visual inspection of Figure 1, that including a seasonal component in most models is necessary. Most of the selected countries, with the exception of Brazil, Chile, Iceland and Philippines, have at least one significant seasonal dummy, and in almost all cases the F-statistic is higher than its critical value (i.e. 2.70 for the full sample); most of the $R^2$s are reasonable with the exception of the four countries to which we have just referred. Therefore, the null hypothesis of all seasonal dummies being non-significant is commonly rejected at the 5% level of significance. This is also true for the US and the

EU countries, which are considered as the control group. Consequently, a seasonal component is included in all the models reported below.

**[FIGURE 1] AND [TABLE 1]**

### 4.3 Empirical Evidence: Whole Model

Figure 1 clearly highlights a persistent downward trend over the period of investigation in all cases. We implement the intervention technique as explained above to assess if, following the implementation of IT, there was a significant downward shift once and for all in the series of inflation. Multivariate STMs are preferred to carry out intervention analysis with control groups. The inclusion of the latter is predicated on the assumption that the inflation series of the countries included in the control group are reasonably correlated with the inflation series of the countries of interest so that the model takes advantage of this correlation. It is sensible, therefore, to expect common factors between IT and non-IT countries. In fact, as reported in Table 2, the correlation coefficients between the inflation rates of the IT countries and non-IT countries included in our sample, are in most cases with a complete span higher than 0.3, for all the countries with data series spanning for the whole period. There is one exception, nonetheless, in the case of Hungary (and to a lesser extent Brazil), which portrays a very low correlation coefficient. It is for this reason that we estimate a univariate model for this country also.

**[TABLE 2]**

In Table 3, we report the main summary statistics, designed to diagnose the performance of the model depicted in equations (2) to (4). H(h) is a test for heteroscedasticity, and it is distributed approximately as F(h,h), where h differs depending on the period of estimation in each country; DW is the Durbin-Watson statistic, which, in a correctly specified model, is approximately distributed as N(2, 4/T), where T is the number of observations; Q(P,d) is the Box-Lung Q-statistic based on the first P residual autocorrelations and distributed approximately as $\chi^2$ with d degrees of freedom, where d is equal to (P + 1 - the number of parameters); seasonality is tested utilizing a $\chi^2$ statistic with 3 degrees of freedom, which tests the null hypothesis of no-seasonality only if the seasonal pattern is persistent throughout the series. However, as the seasonal pattern usually changes relatively slowly, this statistic is used only as a guide to the relative importance of the seasonal effects. $R_S^2$ is the coefficient of determination, calculated as $R_S^2 = 1 - \left[(T-d)\cdot \tilde{\sigma}^2 / SSDSM\right]$, where SSDSM stands for the sum of squared errors obtained by subtracting the seasonal mean from the dependent variable in differences (Koopman, el al., 1999). We also report in the second part of each country's table and under 'Component', the standard deviations of the disturbances that drive the different components for all series in the models, called in the literature the hyperparameters (Harvey, 1989). The mnemonics are as follows: Irr stands for 'irregulars', and estimates the standard deviations of pertubations in the measurement equation ($\tilde{\sigma}^2_{\varepsilon_{it}}$); Lvl corresponds to the standard deviations of the perturbations driving levels ($\tilde{\sigma}^2_{\eta_{it}}$); Slp accounts for the estimation of the standard deviations of errors corresponding to slopes ($\tilde{\sigma}^2_{\zeta_{it}}\ \zeta_t$); and Sea stands for the estimated the standard deviations of the seasonal perturbations ($\tilde{\sigma}^2_{\kappa_{it}} = \tilde{\sigma}^2_{\kappa^*_{it}}$).

**[TABLE 3]**

Heteroscedasticity is not a problem in the case of all countries at the 1% significance level. The Durbin-Watson statistic rejects the hypothesis of autocorrelation except in the case of South Korea. The Box-Lung Q statistic is below the critical value at the 1% level (16.81) in most cases, with the exception of Chile, Iceland, Mexico, Poland,Thailand and for both countries acting as control group in the cases of Philippines and Iceland. We content that, in general, neither is there a serious problem of autocorrelation. The seasonality statistic rejects the absence of seasonality patterns in the 'control-group' case at the 1% level of significance in most multivariate cases. In Iceland and the Philippines we do not include this component, as mentioned below. The same occurs in six of the nine IT cases, for which data cover the whole period of estimation. The three countries that constitute the exception are: Chile, Philippines and Thailand. In view of the fact that there is always at least one of the three countries in each model with significant seasonals, and also that not incorporating this component would have serious implications for the autocorrelation of the series, we conclude that accounting for the seasonal components in all models is pertinent. For those countries with a shorter span of available data we only include this component if in the first estimation under the general model, the results produce a standard deviation for this component, which is different from zero. It is for this reason that Brazil, Mexico, Peru and Poland do not present this component in the final model. Similarly, the slope component is dropped in those cases for which the standard deviation was not different from zero, again if the available data were for a shorter period than that covered by the data of the full period. It is again for this reason that the simpler Local Level Model is estimated for the cases of Brazil, the

Czech Republic, Mexico, Peru and Poland. Most $R^2$s appear to be reasonable. In the first instance, however, $R^2$s computed for Iceland and Philippines were worryingly low, so we applied the simpler Local Level Model without seasonals, with significantly better results. All the 'components' present reasonable values on the whole, with one notable exception, this being the case of Colombia against the EU when the slp is zero. It is also worth noting that after accounting for these changes, the results relating to intervention analysis, which are further discussed in section 4.3, vary very little, if at all.

**4.4 Empirical Evidence: IT Intervention**

Table 4 and Figure 2 report the results regarding the IT implementation. We provide the dates when intervention started in each country, as shown in the first and second columns of the table. Estimations corresponding to the model in its multivariate form follow. The estimates for the intervention parameter $\delta$ in the measurement equation are cited in the third column for each country. Root mean squared errors (RMSE), t- and p-values are reported in the next three columns. The seventh column, labeled 'Common Factors', cites how many and which common factors are evident in the multivariate model. Regarding multivariate STMs three out of eight cases did not present common factors at all, these being Iceland, Israel and Peru. For the rest, common trends ((labeled as 'CFT') constitute a typical feature. Models that contain CFTs are always estimated along with other common factors such as seasonals (labeled as 'CFSE') and slopes (labeled as 'CFSL').

In Table 4 the estimated coefficients for the intervention parameter in each IT country are included in the third column under the label 'Coefficient', with the t- and p-values in the two columns next to that of the coefficients. We first wish to highlight the result that in most of the cases the sign of the intervention coefficient is negative, while in two cases the coefficient is positive but insignificant; South Africa is the exception with a significantly positive effect following the IT implementation. This striking feature may be explained by the significant effect of a supply-side shock on inflation following a more than 34% depreciation of the rand in the second half of 2001. Such phenomenon, and the increase in food and oil prices, raised inflation expectations and pushed up the CPI quite substantially towards the end of 2001, reaching its pick in 2002(Q2). Subsequently, this triggered a substantial monetary tightening, which had an impact on inflation after a delay of around 4 quarters, as it can be observed in Figure 1. As a result, the high inflation rates reached after the intervention are captured by a positive coefficient, but a decreasing trend is depicted thereafter.

In fact, the estimated results may be divided into four groups. In the first of these, following the implementation of IT, Colombia, Israel and South Korea present a significant decrease in inflation once and for all at the 5% level of significance. A second group is composed by the Czech Republic and Thailand, two cases with t-values that indicate that the relevant coefficients only just miss being statistically significant. The third category is filled by the case of South Africa, which presents a significantly positive impact of IT on the series of inflation. The rest of the countries compose the forth group: Brazil, Chile, Hungary, Iceland, Mexico, Peru, Poland and the Philippines. This group is characterized by a downward trend in inflation, which commences before the IT imposition, so that when IT was introduced inflation had already been tamed. These cases have the common characteristic of having insignificant intervention coefficients, with a negative sign for intervention in most of the cases (exceptions are Peru and Poland). In Figure 2 the dates of IT imposition are recorded along with the point of intervention, indicated with a vertical bar. These figures show a noticeable downward step-change for all countries pertaining to the first two aforementioned groups, and it is also remarkable how evident the upward step in the case of South Africa is. This is especially noticeable when compared with the control group, which shows a smooth on-going trend at each point of intervention. In most of the rest of the cases, a more modest decrease at the point of intervention is evident (see Brazil, Chile, Hungary, Mexico, the Philippines), and some of them show no relevant change in their trends after intervention.

**[TABLE 4] AND [FIGURE 2]**

We may therefore conclude on the effect of IT implementation that the results are mixed to say the least. The general picture that emerges from Figures 2 along with the results reported in Table 4 is that IT appears to have been introduced after the countries included in our sample had already managed to tame inflation. However, inflation patterns of the IT countries converged to those of the countries included in the control group, following the introduction of IT. Consequently, the conclusion that IT was totally ineffective may be too hasty. For it is the case that although IT does not appear to have been significantly effective when introduced in the majority of cases, subsequent persistence in its implementation may have produced a 'lock-in' effect for price inflation. Given the determination of central banks to conquer and maintain price stability, inflation expectations may have so changed that subsequent levels of inflation may have been contained within the IT limits. Indeed, a number of authors (Bernanke et al., 1999; Corbo et al., 2002; Petursson, 2004) have argued that IT was a great deal more successful in 'locking-in' low levels of inflation, rather than actually achieving lower inflation rates. We explore this distinct possibility in the rest of the paper.

### 4.5 Empirical Evidence: The 'Lock-In' Effect

We begin by testing for the differences in the standard deviations of inflation that correspond to the two periods under investigation: the period prior to the imposition of IT and the period subsequent to intervention. Table 5 presents these results for countries, which implemented IT, and we do the same for those countries we include in the control group. We consider for the latter the different dates at which IT was first implemented in the corresponding IT country.[6] Standard deviations are significantly different for both periods in most of the countries implementing IT at the 1% level of significance (eleven out of the fourteen cases). They are of course a great deal lower in the post-IT period as one should expect. Similar 'lock-in' results are evident in the case of EU in relation to the tests implemented in this section (ten out of fourteen and at all three levels of significance), but differences in standard deviations are present in a much lesser extent in the US. Superficially the results in this table would support the hypothesis of significant 'lock-in' effects in IT countries. More tests, however, are provided below.

**[TABLE 5]**

We proceed by offering further tests for the possibility of 'lock-in' effects by applying STMS for the period prior to intervention ($t=1,\ldots,\tau-1$). Then, one-step ahead predictions are undertaken for $t=\tau+1,\ldots,T$, and these are compared with the actual values of

[6] This raises the issue of the 'break date' for the two non-IT countries. Ball and Sheridan (2003), for example, use the average adoption date for the IT countries (see, also, IMF, 2005; Scott and Stone, 2005). We believe that our approach of using the 'break date' of the IT country in question for the two non-IT countries is more satisfactory, for it avoids the issue of arbitrariness embedded in the other approaches.

inflation. As a result of this procedure, we compute standardized one step-ahead prediction errors $\left(\tilde{v}_t\right)$, where $\tilde{v}_t = {v_t}/{f_t^{1/2}}$, and $v_t$ is the one-step ahead prediction error with $f_t$ being the estimate of its variance (Harvey, 1989, p. 289). Graphical procedures and statistical tests are also employed to examine the possibility of 'lock-in' effects.

We begin with CUSUM plots, which provide an initial impression of how inflation evolved after intervention. The following formula is utilized:

$$CUSUM(t,\tau) = \sum_{j=\tau+1}^{t} \tilde{v}_j \tag{5}$$

where the symbols are as above. The graphs for each country of this formula depict the path of the cumulative standardized residuals. Should the plots be, for instance, always positive and systematically increasing, a break away possibility from 'lock-in' might be evident. Such a case could be interpreted as evidence against the lock-in effect, since actual inflation rates would be systematically under-predicted by the model. Mutatis mutandis, in the case of negative and systematically decreasing plots the model would be over-predicting.

Figure 3 shows CUSUM plots for all IT countries considered. A common pattern in these graphs is that no substantive or steady trend is obvious in any of the countries studied and, especially, that none of them marks any important presence on the positive side of the graph. There is, instead, some evidence in favor of the application of IT, as most of the plots in IT countries are below the zero line, but none of them crosses the significance lines and all plots tend to revert to a zero mean. This evidence can be interpreted as successful implementation of monetary policies in preventing inflation from bouncing back to previously registered high levels, or even to lower levels than those predicted by the model estimated up to intervention. These results, however, should be considered with caution as CUSUM is best regarded as a diagnostic rather than a formal test procedure (Harvey and Durbin, 1986).

In Table 6 formal statistical tests are portrayed. CUSUM-t tests are applied to the 14 IT countries, as well as to the two non-IT countries. The CUSUM-t test provides an assessment of the CUSUM plots. It is calculated as:

$$CUSUM = (T-\tau)^{-1/2} \cdot \sum_{j=\tau+1}^{t} \tilde{v}_j \tag{6}$$

and is distributed as a t-statistic with (T-τ) degrees of freedom; the symbols are again as above. This t-statistic should be used when there is suspicion of possible 'breakaways' of a certain sign. In this case the t-statistic is used to test if, following intervention, there is a consistent pattern that would suggest failure to control inflation at the level that the model would predict should there not be any change in the monetary strategy. If any systematic pattern of 'breakaway' were noticeable, this would be taken as evidence of absence of a 'lock-in' effect.

The results for this test are reported in Table 6. For each model CUSUM-t statistics are calculated both for IT countries and for the control group. These statistics, as mentioned above, are distributed as $t_{T-\tau}$ and reported for IT countries in the first column of Table 6.

According to these statistics 'breakaways' are rejected in all IT cases as they are well below the critical value at the 5% level of significance, with the exception of Israel. In this case, as it is shown in Figure 3, the cusum-plot falls below the significance line. This piece of evidence reveals a significant decrease of actual values from the magnitudes predicted before intervention, which occurs immediately after the implementation of IT. It is clear, though, that the inflation rate in Israel reverts back to the zero line by the end of the estimation period. Turning to the 'control group' countries, similar results are evident as in the case of most of the IT countries. As reported in the second and third columns of Table 6, this occurs to all models (with the exception of the EU vis-á-vis Israel) and, therefore, for all dates for which IT was implemented. Clearly, the CUSUM t-values computed for the different cases examined relating to the EU and the US, are also well below their critical values.

**[TABLE 6] AND [FIGURE 3]**

We are, therefore, able to derive two important conclusions on the basis of these results. The first is that IT has been a success story in 'locking-in' inflation rates and thus avoiding a 'bounce-back' in inflation in the 14 countries considered for the purposes of this paper. The second is that a similar conclusion is applicable in the case of the two countries included in the control group. This clearly indicates that it may very well be the case that the 'lock-in' effect alluded to in this paper may be due to other factors than IT intervention. Interestingly enough, Ball and Sheridan (2003) reach a similar conclusion utilizing a completely different approach and technique (see, also, Johnson, 2002, 2003).

## 5. Summary and Conclusions

We have attempted in this study to gauge empirical evidence for the 14 emerging countries that adopted the new monetary policy strategy that has come to be known as IT. In this endeavour we have applied Intervention Analysis to the multivariate STM approach. This is an important exercise, we would suggest, in view of the prevailing view that IT has gone hand-in hand with low inflation rates (King, 1997; Bernanke, 2003a, 2003b). We have demonstrated that although this is definitely the case, IT was introduced well after inflation had begun its downward trend. We have argued, though, that there is still the distinct possibility that IT 'locks in' low inflation rates. This is indeed the case for the IT countries. But then we have also produced evidence that suggests that non-IT central banks have also been successful in achieving and maintaining consistently low inflation rates. Just as we concluded in another study that deals with industrialised OECD countries (Angeriz and Arestis, 2005), in this paper, too, the evidence we have produced clearly suggests that a central bank does not need to pursue an IT strategy to achieve and maintain low inflation.

A final comment on the experience of IT emerging countries is that whatever 'success' they may have had ought to be set against the background of the 'preconditions' that need to be met before IT adoption. IMF (2005) summarizes these pre-conditions as follows: technical capability of the central bank in implementing IT; an efficient institutional set up to motivate and support the commitment to low inflation, including institutional independence; a healthy financial system; an economic structure characterised with fully deregulated prices; and absence of fiscal dominance. On current evidence, these preconditions admittedly do not prevail in most, if not all cases (IMF, 205; but see Jonas and Mishkin, 2005, for a more neutral view on the importance of preconditions). Under such circumstances, the IT framework may be highly unsuitable for these countries. This argument clearly strengthens the finding of this paper that whatever success we may attach to fighting inflation in the IT emerging countries, it cannot be due to this strategy. Other factors than IT must surely be responsible for the lower rates of inflation achieved by these countries. The opposite argument may also be true. Adoption of the IT strategy by these countries may lead to an improvement of the institutional 'preconditions'. But the experience with the emerging IT countries is by far too short for an assessment of this hypothesis to be undertaken persuasively.

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## Table 1. Significance of seasonal dummies

| | Q1+ | Q2 | t-statistic++ | Q3 | t-statistic++ | Q4 | t-statistic++ | Obs. | $R^2$ | F(3,T-3) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Brazil** † | 0.110 | -0.457 | (-0.84) | -0.284 | (-0.52) | 0.631 | (1.15) | 39 | 0.06 | 0.77 |
| **Chile** | -0.786 | 0.356 | (0.86) | 0.520 | (1.25) | -0.090 | (-0.22) | 99 | 0.02 | 0.78 |
| **Colombia** | 3.674 | -1.989 | (-3.74)* | -2.571 | (-4.84)* | 0.886 | (1.67)*** | 99 | 0.30 | 13.39* |
| **Czech Republic** † | 2.741 | -2.202 | (-3.32)* | -0.137 | (-0.21) | -0.402 | (-0.63) | 54 | 0.18 | 3.83** |
| **Hungary** † | 3.779 | -3.284 | (-5.23)* | -1.211 | (-1.97)** | 0.715 | (1.16) | 98 | 0.26 | 10.86* |
| **Iceland** | 0.418 | 0.363 | (0.74) | -0.635 | (-1.29) | -0.146 | (-0.30) | 99 | 0.02 | 0.77 |
| **Israel** † | -0.273 | 1.068 | (2.45)* | -0.986 | (-2.27)** | 0.191 | (0.44) | 75 | 0.14 | 3.78** |
| **Mexico** † | 1.489 | -2.778 | (-3.90)* | -0.259 | (-0.36) | 1.548 | (2.18)** | 99 | 0.17 | 6.69* |
| **Peru** † | 3.873 | -2.445 | (-3.44)* | -0.462 | (-0.65) | -0.966 | (-1.36) | 55 | 0.21 | 4.70* |
| **Philippines** | 0.025 | -0.361 | (-0.74) | 0.750 | (1.53) | -0.413 | (-0.84) | 99 | 0.04 | 1.2 |
| **Poland** † | 2.875 | -2.424 | (-3.01)* | -2.68 | (-3.45)* | 2.228 | (2.87)* | 58 | 0.35 | 9.72* |
| **South Africa** | 0.811 | -0.408 | (-1.44) | 0.427 | (1.51) | -0.831 | (-2.94)* | 99 | 0.12 | 4.33* |
| **South Korea** | 2.312 | -1.651 | (-4.92)* | 0.283 | (0.84) | -0.943 | (-2.81)* | 99 | 0.26 | 10.95* |
| **Thailand** | 1.185 | -0.074 | (-0.29) | -0.172 | (-0.67) | -0.939 | (-3.65)* | 99 | 0.13 | 4.62* |
| **EU** | 0.34 | -0.173 | (2.70)* | -0.38 | (5.93)* | 0.213 | (3.32)* | 99 | 0.36 | 17.84* |
| **US** | 0.893 | -0.234 | (1.40) | -0.109 | (0.66) | -0.55 | (3.31)* | 99 | 0.12 | 4.84* |

Notes: The time span in all countries is 1980(Q1)-2004(Q4), with he exception of those marked by †, for which it differs from country to country as follows: Brazil: 1995(Q1)-2004(Q4), Czech Republic: 1991(Q2)-2004(Q4), Hungary: 1980(Q2)-2004(Q4), Israel: 1986(Q1)-2004(Q4), Mexico: 1989(Q1)-2004(Q4), Peru: 1991(Q1)-2004(Q4), and Poland: 1991(Q1)-2004(Q4).

+ Q1 is computed so that all dummy effects add up to 0.
++ The numbers in these columns represent values for the t statistics (as in parentheses).
* Significant at the 1% significant level.
** Significant at the 5% significant level.

## Table 2. Correlation coefficients between inflation rates in IT and non-IT countries

| | EU | US |
|---|---|---|
| **Brazil** | 0.24 | 0.01 |
| **Chile** | 0.48* | 0.28* |
| **Colombia** | 0.45* | 0.39* |
| **Czech Republic** | 0.45* | 0.31** |
| **Hungary** | -0.00 | 0.09 |
| **Iceland** | 0.75* | 0.40* |
| **Israel** | 0.50* | 0.26** |
| **Mexico** | 0.29* | 0.06 |
| **Peru** | 0.61* | 0.19 |
| **Philippines** | 0.32* | 0.23** |
| **Poland** | 0.66* | 0.24*** |
| **South Africa** | 0.40* | 0.35* |
| **South Korea** | 0.51* | 0.71* |
| **Thailand** | 0.45* | 0.60* |

Notes: The period of estimation is as reported under Notes in Table 1.

* Test of independence of the variables rejected at 1%;
** Test of independence of the variables rejected at 5%.
*** Test of independence of the variables rejected at 10%.

**Table 3. Summary statistics for the estimated STM Models**

| | Brazil |
|---|---|
| H(13) | 2.229 |
| DW | 1.706 |
| Q(7,6) | 4.679 |
| Rs^2 | 0.182 |
| ***Component*** | |
| Irr | 1.069 |
| Lvl | 0.929 |

| | EU | US | Colombia |
|---|---|---|---|
| H(31) | 0.836 | 0.494 | 0.535 |
| DW | 1.697 | 1.762 | 1.811 |
| Q(9,6) | 12.162 | 7.865 | 12.453 |
| Seasonality | 24.643* | 27.621* | 114.495* |
| Rs^2 | 0.210 | 0.331 | 0.394 |
| ***Component*** | | | |
| Irr | 0.204 | 0.519 | 1.442 |
| Lvl | 0.099 | 0.061 | 0.165 |
| Slp | 0.000 | 0.025 | 0.031 |
| Sea | 0.013 | 0.026 | 0.044 |

| | EU | US | Chile |
|---|---|---|---|
| H(31) | 0.721 | 0.408 | 0.125 |
| DW | 1.819 | 2.054 | 1.773 |
| Q(9,6) | 9.833 | 5.308 | 17.239 |
| Seasonality | 21.05* | 37.66* | 5.74 |
| Rs^2 | 0.285 | 0.412 | 0.164 |
| ***Component*** | | | |
| Irr | 0.197 | 0.471 | 1.360 |
| Lvl | 0.011 | 0.043 | 0.840 |
| Slp | 0.020 | 0.026 | 0.035 |
| Sea | 0.013 | 0.026 | 0.011 |

| | Czech Republic |
|---|---|
| H(17) | 0.058 |
| DW | 1.709 |
| Q(8,6) | 12.953 |
| Seasonality | 10.423** |
| Rs^2 | 0.264 |
| ***Component*** | |
| Irr | 1.727 |
| Lvl | 0.210 |
| Sea | 0.036 |

| | Hungary |
|---|---|
| H(31) | 0.190 |
| DW | 2.013 |
| Q(9,6) | 3.615 |
| Seasonality | 4.107 |
| Rs^2 | 0.441 |
| ***Component*** | |
| Irr | 1.121 |
| Lvl | 0.540 |
| Slp | 0.014 |
| Sea | 0.248 |

| | EU | US | Iceland |
|---|---|---|---|
| H(33) | 0.454 | 0.602 | 0.089 |
| DW | 1.732 | 1.903 | 1.958 |
| Q(9,6) | 71.613 | 21.534 | 28.335 |
| Rs^2 | 0.811 | 0.293 | 0.741 |
| ***Component*** | | | |
| Irr | 0.274 | 0.593 | 1.158 |
| Lvl | 0.142 | 0.190 | 1.846 |

| | EU | US | Israel |
|---|---|---|---|
| H(24) | 0.995 | 0.933 | 0.615 |
| DW | 2.045 | 1.958 | 2.224 |
| Q(8,6) | 18.687 | 2.498 | 12.228 |
| Seasonality | 16.96* | 40.37* | 8.97** |
| Rs^2 | 0.374 | 0.392 | 0.418 |
| **Component** | | | |
| Irr | 0.174 | 0.342 | 1.326 |
| Lvl | 0.076 | 0.123 | 0.248 |
| Sea | 0.014 | 0.032 | 0.017 |

| | Mexico |
|---|---|
| H(21) | 0.1728 |
| DW | 1.7250 |
| Q(9,6) | 20.387 |
| Rs^2 | 0.3362 |
| ***Component*** | |
| Irr | 1.5409 |
| Lvl | 1.4983 |

| | Peru |
|---|---|
| H(18) | 0.039 |
| DW | 1.556 |
| Q(7,6) | 13.018 |
| Rs^2 | 0.837 |
| ***Component*** | |
| Irr | 0.839 |
| Lvl | 2.687 |

| | EU | US | Philippines |
|---|---|---|---|
| H(33) | 0.457 | 0.616 | 0.046 |
| DW | 1.717 | 1.999 | 1.982 |
| Q(9,8) | 68.239 | 23.227 | 12.573 |
| Rs^2 | 0.811 | 0.288 | 0.262 |
| ***Component*** | | | |
| Irr | 0.274 | 0.589 | 1.336 |
| Lvl | 0.142 | 0.172 | 1.603 |

| | Poland |
|---|---|
| H(18) | 0.035 |
| DW | 0.841 |
| Q(7,6) | 23.312 |
| Rs^2 | 0.621 |
| ***Component*** | |
| Irr | 2.117 |
| Lvl | 1.257 |

| | EU | US | South Africa |
|---|---|---|---|
| H(31) | 0.723 | 0.398 | 1.182 |
| DW | 1.921 | 2.070 | 1.776 |
| Q(9,6) | 12.173 | 5.525 | 6.852 |
| Seasonality | 20.117* | 36.260* | 14.407* |
| Rs^2 | 0.315 | 0.412 | 0.378 |
| ***Component*** | | | |
| Irr | 0.184 | 0.469 | 1.029 |
| Lvl | 0.080 | 0.069 | 0.001 |
| Slp | 0.012 | 0.025 | 0.017 |
| Sea | 0.013 | 0.025 | 0.017 |

| | EU | US | South Korea |
|---|---|---|---|
| **H(31)** | 0.704 | 0.423 | 0.353 |
| **DW** | 1.791 | 2.010 | 1.503 |
| **Q(9,6)** | 9.996 | 5.302 | 11.449 |
| **Seasonality** | 20.488* | 31.141* | 53.233* |
| **Rs^2** | 0.295 | 0.501 | 0.311 |
| ***Component*** | | | |
| **Irr** | 0.192 | 0.461 | 0954 |
| **Lvl** | 0.027 | 0.019 | 0.041 |
| **Slp** | 0.019 | 0.0266 | 0.088 |
| **Sea** | 0.014 | 0.028 | 0.018 |

| | EU | US | Thailand |
|---|---|---|---|
| **H(31)** | 0.671 | 0.526 | 0.495 |
| **DW** | 1.859 | 1.920 | 1.867 |
| **Q(9,6)** | 10.101 | 5.256 | 30.365 |
| **Seasonality** | 19.29* | 34.78* | 5.98 |
| **Rs^2** | 0.292 | 0.465 | 0.252 |
| ***Component*** | | | |
| **Irr** | 0.194 | 0.470 | 0.870 |
| **Lvl** | 0.028 | 0.041 | 0.009 |
| **Slp** | 0.019 | 0.024 | 0.051 |
| **Sea** | 0.014 | 0.027 | 0.043 |

Notes: The period of estimation is as reported under Notes in Table 1.

* Null of non-seasonality rejected at 1%;

** Null of non-seasonality rejected at 5%.

**Table 4. Intervention Estimates**

| | | Multivariate | STM | estimates | | |
|---|---|---|---|---|---|---|
| | Dates of Intervention | Coefficient | RMSE | t-value | p-value | Common Factors |
| **Brazil** | 1999/Q2 | -0.8277 | 1.472 | -0.562 | [0.58] | Univariate |
| **Colombia** | 1999/Q3 | -3.5658 | 0.546 | -6.530 | [0.00] | 2CFT, CFSE |
| **Chile** | 1991/Q1 | -1.3264 | 1.541 | -0.861 | [0.39] | CFT, CFSL |
| **Czech Republic** | 1998/Q1 | -1.4125 | 0.856 | -1.649 | [0.11] | Univariate |
| **Hungary** | 2001/Q3 | -0.9058 | 1.231 | -0.736 | [0.46] | Univariate |
| **Iceland** | 2001/Q1 | -0.5536 | 2.120 | -0.261 | [0.79] | NO |
| **Israel** | 1992/Q1 | -1.7632 | 0.731 | -2.411 | [0.02] | NO |
| **Mexico** | 1999/Q1 | -1.0516 | 2.266 | -0.464 | [0.64] | Univariate |
| **Peru** | 1994/Q1 | 0.2547 | 0.803 | 0.317 | [0.75] | Univariate |
| **Philippines** | 2002/Q1 | -0.4253 | 2.198 | -0.194 | [0.85] | NO |
| **Poland** | 1999/Q1 | 0.6988 | 2.356 | 0.626 | [0.53] | Univariate |
| **South Africa** | 2000/Q1 | 0.9763 | 0.467 | 2.092 | [0.04] | 2CFT, CFSL, 2CFSE |
| **South Korea** | 1998/Q1 | -0.9935 | 0.497 | -1.999 | [0.05] | 2CFT, CFSL |
| **Thailand** | 2000/Q2 | -0.6427 | 0.448 | -1.436 | [0.15] | 2CFT, CFSL |

Notes: The period of estimation is as reported under Notes in Table 1.
The acronyms in the last column have the following meaning: CFT refers to common trends, CFSE refers to common seasonals, and CFSL refers to common slope components.

**Table 5. Standard deviations in pre-IT and post-IT periods**

| | IT-Country | IT-Country | Non-IT EU | Non-IT EU | Non-IT US | Non-IT US |
|---|---|---|---|---|---|---|
| | Pre-IT | Post-IT | Pre-IT | Post-IT | Pre-IT | Post-IT |
| **Brazil** | 2.004 | 1.638 | 0.303 | 0.272 | 0.352 | 0.709* |
| **Colombia** | 2.492 | 0.289* | 0.839 | 0.275* | 0.801 | 0.725 |
| **Chile** | 2.47 | 1.40* | 0.865 | 0.363* | 0.945 | 0.508* |
| **Czech Republic** | 2.499 | 1.184* | 0.362 | 0.279 | 0.327 | 0.647* |
| **Hungary** | 3.086 | 0.991* | 0.779 | 0.275* | 0.684 | 0.806 |
| **Iceland** | 4.896 | 1.061* | 0.833 | 0.309* | 0.786 | 0.785 |
| **Israel** | 1.636 | 1.57 | 0.312 | 0.328 | 0.575 | 0.525 |
| **Mexico** | 7.701 | 0.975* | 0.838 | 0.275* | 0.81 | 0.693 |
| **Peru** | 9.083 | 1.014* | 0.309 | 0.284 | 0.244 | 0.560* |
| **Philippines** | 2.914 | 0.678* | 0.833 | 0.309* | 0.786 | 0.785 |
| **Poland** | 5.607 | 0.697* | 0.401 | 0.275** | 0.401 | 0.693* |
| **South Africa** | 1.318 | 1.1274 | 0.842 | 0.277* | 0.795 | 0.751 |
| **South Korea** | 2.018 | 1.126* | 0.823 | 0.279* | 0.848 | 0.647*** |
| **Thailand** | 4.377 | 0.572* | 0.839 | 0.283* | 0.794 | 0.724 |

Notes: The period of estimation is as reported under Notes in Table 1.

* The null of equal variances rejected at a 1% significant level.

** The null of equal variances rejected at a 5% significant level.

*** The null of equal variances rejected at a 10% significant level.

**Table 6. Predictive capacity of models: CUSUM t-test**

| | IT Country | EU | US | Degrees of freedom |
|---|---|---|---|---|
| **Brazil** | 0.96 | | | 23 |
| **Colombia** | 0.542 | 0.210 | 0.235 | 22 |
| **Chile** | -0.381 | -0.296 | -0.371 | 56 |
| **Czech Republic** | -1.508 | | | 28 |
| **Hungary** | -0.122 | | | 17 |
| **Iceland** | 0.011 | -0.582 | -0.082 | 16 |
| **Israel** | 2.585* | -3.967* | 1.530 | 52 |
| **Mexico** | -0.004 | 0.646 | 0.388 | 24 |
| **Peru** | -0.255 | | | 44 |
| **Philippines** | 0.222 | 0.157 | 0.618 | 12 |
| **Poland** | -0.068 | | | 24 |
| **South Africa** | 1.438 | 0.729 | 0.067 | 20 |
| **South Korea** | -0.978 | 1.246 | 1.159 | 28 |
| **Thailand** | -0.267 | 0.714 | -0.267 | 19 |

Notes: The period of estimation is as reported under Notes in Table 1.

* Failures detected at the 5% significant level (this is a t-distribution with critical values ranging from 2.09 for 19 degrees of freedom and 2.01 for 56 degrees of freedom).

# TABLES AND FIGURES

## Figure 1. Inflation (% change in CPI)

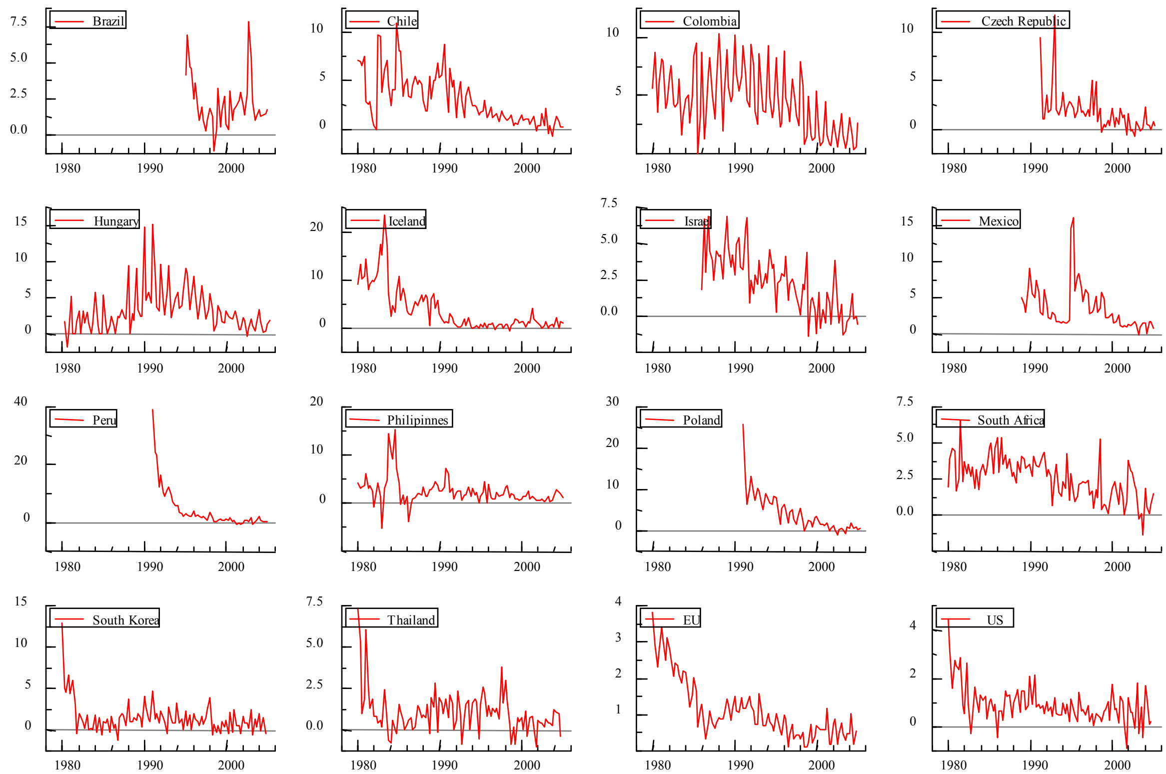
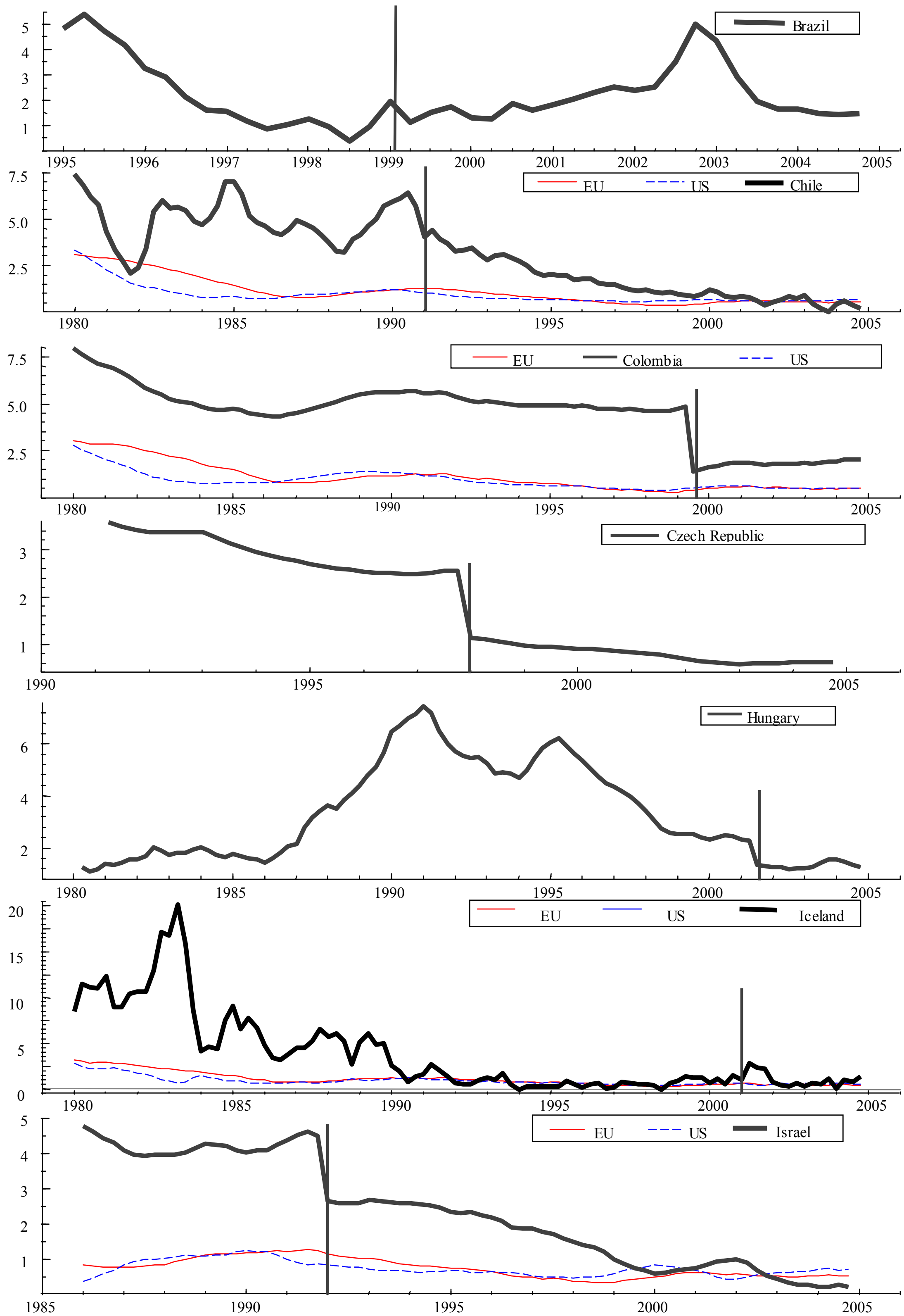
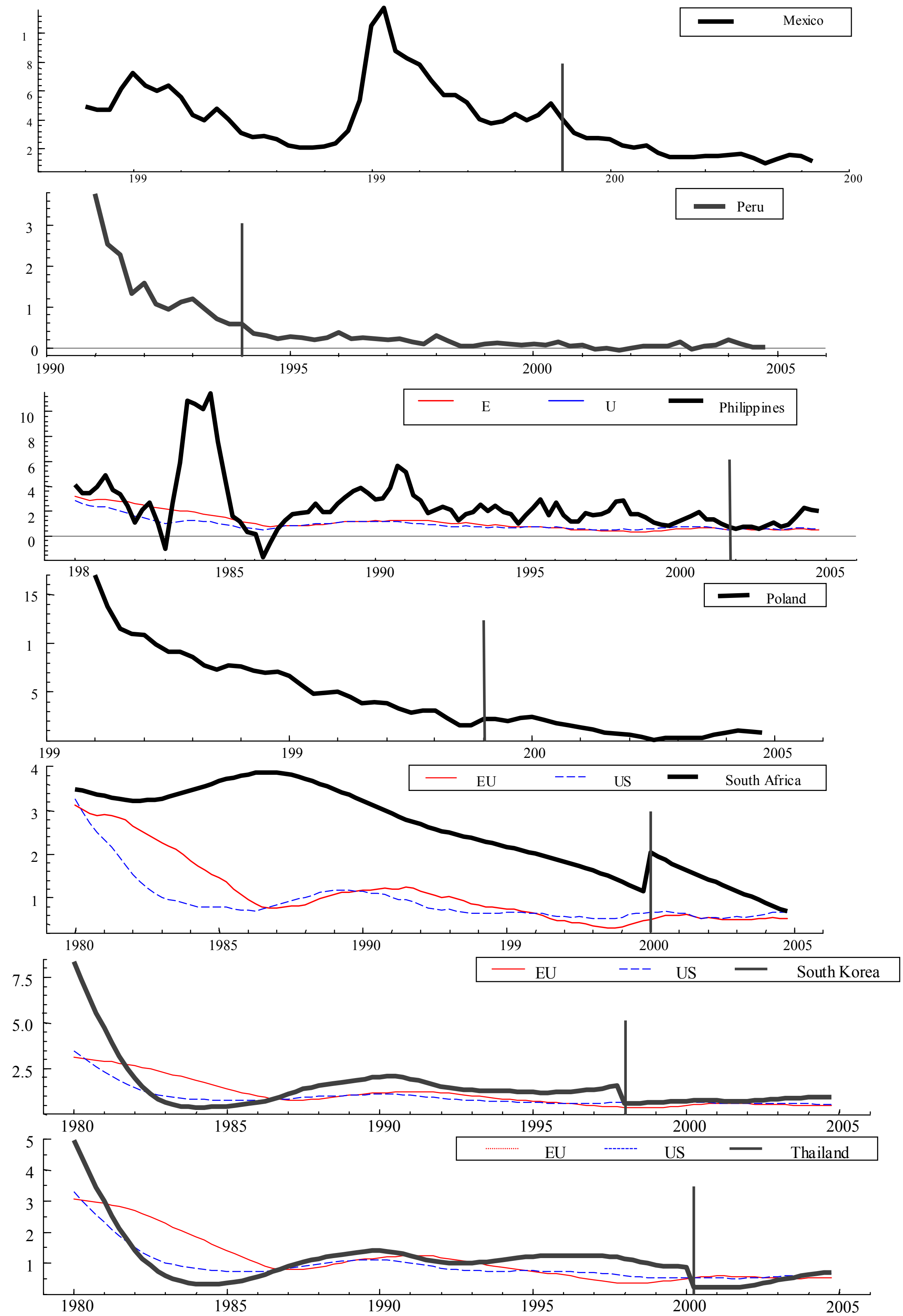


**Figure 2. Trends and interventions in IT and non-IT countries (%)**




Mexico
Peru
1990
1995
2000
2005
E
U
Philippines
Poland
EU
US
South Africa
1980
1985
1990
2005
EU
US
South Korea
EU
US
Thailand

## Figure 3. Plot of CUSUM standardized residuals