ASSESSING INFLATION TARGETING THROUGH INTERVENTION ANALYSIS

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Abstract

The aim of this paper is to deal with the empirical aspects of the 'new' monetary policy framework, known as Inflation Targeting. Applying Intervention Analysis to multivariate Structural Time Series models, new empirical evidence is produced in the case of a number of OECD countries,. 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. But, then, Inflation Targeting 'locks in' low inflation rates. The evidence produced in this paper suggests that non-IT central banks have also been successful on this score.

JEL Classification: E31, E52

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

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1. Introduction

Inflation Targeting (IT) is a 'new' monetary policy framework, which has been increasingly accepted by a number of countries around the globe ever since New Zealand introduced it in 1990. A number of studies have examined empirically the extent of the impact of IT on inflation and on other variables, typically GDP, in a number of countries. The studies that deal with the empirical aspects of IT, ask a number of questions with the most pertinent being whether IT improves inflation performance, tackles inflation persistence, and constrains inflationary expectations. It would not be an exaggeration, though, to suggest that the empirical results of IT investigation are at best mixed (Johnson, 2002, 2003; Levin et al., 2004; Ball and Sheridan, 2003).

In view of the mixed nature of these results, we attempt to remove some of the uncertainty surrounding them. In this endeavour we apply Intervention Analysis to multivariate Structural Time Series Models (STMs), as set out in Harvey (1996). To our knowledge, this technique has not been used in Economics with the exception of Harvey and Bernstein (2003a), and it has certainly not been utilized in the relevant literature of IT. Multivariate STMs are particularly relevant to IT since they "are shown to provide an ideal framework for carrying out intervention analysis with control groups" (Harvey, op. cit., p. 313). This is precisely what IT models are designed to achieve.

We proceed as follows. In section 2 we elaborate on the methodology underlying this technique, which is utilized throughout this paper. Section 3 reports on the empirical results obtained, and section 4 summarizes and concludes.

2. Methodology

2.1 Main ingredients

We assess the impact of the adoption of IT by applying Intervention Analysis to multivariate STMs. This framework formulates time series models in terms of their most noticeable features, this being a set of 'unobserved components' with specific dynamic properties, such as trends, seasonals and short-run shocks. We begin our explanation of these models by noting that "the basic idea of structural time series models is that they are set up as regression models in which the explanatory variables are functions of time, but with coefficients which change over time. Model specification proceeds on the basis that the researcher has a good idea of what components to include from the outset, though any model will always be subject to diagnostic checking" (Harvey, 1996, p. 317). As we describe below, these 'unobserved components' are treated as stochastic elements, and the relevant variances are estimated. By doing so, a novel element is introduced in relation to other commonly used *ad-hoc* detrending procedures, such as Hodrick-Prescott (1980). The latter are prone to introducing spurious cycles, in a way that the STM methodology does not (Harvey and Jaegger, 1993).

The decomposition of a series in distinctive 'unobserved components' provides an intuitively appealing approach for isolating permanent and transitory changes occurring to the series, such as trends and seasonal effects, from those happening due to specific events identified *a priori* by the investigator, in our case IT interventions. The analysis of the impact of such incidents is known in the literature of Time Series as Intervention Analysis ever since Box-Tiao (1975). The precise identification of the effects due to intervention on a specific time series are facilitated if multivariate STMs are utilized. This technique makes use of information available on both set of countries, that is those that implement the strategy and those that do not implement the strategy. As such, STMs provide a significant advantage, which is related to the 'fundamental problem of causal inference' (Holland, 1986). In other words, 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, thereby presenting the investigator with a logistical problem. Different solutions have been devised to address this problem. For example, the programme evaluation literature pioneered by Rubin (1974) recommends a solution to this problem by providing a 'counterfactual' framework for estimating treatment effects across multiple individuals (see, also, Angrist et al., 1996).

In the context of Time Series, Harvey (1996) suggests incorporating in the model series of units not subjected to intervention, but which contain components that correlate highly with similar ones of the series that are subjected to intervention. Using the former as the control group, it is possible to obtain a more precise measure of the intervention effect. In this context, using auxiliary series not only helps to achieve a more satisfactory decomposition of 'unobserved components', but it also provides a helpful framework for handling control groups. Including in the sample both IT countries and those that do not implement the strategy, goes a long way to alleviating the ‘fundamental problem of causal inference’ to which we alluded above. There are, thus, clear advantages in employing this framework, summarized by Harvey (1996): “Firstly, ... the higher the correlation between the groups, the greater the gain in precision with which the intervention effect may be estimated. Secondly, a control group, which is co-integrated with the experimental group is likely to be very valuable since it enables a consistent estimator to be constructed. Thirdly, although single equation estimation is possible, if appropriate modifications are implemented, it is generally better to work with the full system” (p. 323).

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

2.2 Multivariate Structural Time Series Models

In this approach, countries that have not implemented IT are considered along with those countries that have introduced this form of intervention. The multivariate STM is used to assess the impact of inflation targeting. It is important to note at the outset that for the purposes of this paper we employ the Local Linear Trend version of STM, conveniently generalized to account for intervention analysis. This model consists of a set of equations as follows:

$(1)\ \ \pi_t = \mu_t + \gamma_t + \delta \cdot \omega_t + \varepsilon_t$

$(2)\ \ \mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t$

$(3)\ \ \beta_t = \beta_{t-1} + \zeta_t$

where $\varepsilon_t \sim NID\left(0, \Sigma_{\varepsilon\, NxN}\right);\ \eta_t \sim NID\left(0, \Sigma_{\eta\, NxN}\right);\ \zeta_t \sim NID\left(0, \Sigma_{\zeta\, NxN}\right);$

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

$$E\left(\kappa_t \kappa_t^{'}\right) = E\left(\kappa_t^* \kappa_t^{*}{'}\right) = \Sigma_\kappa \quad and \quad E\left(\kappa_t\, \kappa_t^{*}{'}\right) = 0.$$

Also, π_t is an Nx1 vector, representing inflation levels for N countries in time period t, which, in turn, depends on a number of vectors of 'unobserved components', namely μ_t, γ_t, $\delta \cdot \omega_t$, ε_t, β_t, η_t, ζ_t, κ_t, shown and defined as appropriate in equations (1) to (3). Vector μ_t in the *measurement equation* (1) represents stochastic trends, i.e. levels, corresponding to each of the countries included in the sample, and receives shocks both in its level and slope (β_t), as shown in the *level equation* (2). The *local equation* (3) assumes that (β_t) follows a random walk. γ_t, in the *measurement equation* purports to capture seasonal movements. We may note in this context that a trigonometric form is chosen for the stochastic seasonality, where $\lambda_j = \pi \cdot j/2$, which is a frequency in radians; γ_t represents the current state of the seasonal cycle, while γ_t^* is included by construction for the purpose of defining γ_t, and has no intrinsic importance. ω_t is the intervention variable, where δ registers the impact on inflation following intervention, ε_t are perturbations (or 'irregulars') in the measurement equation, η_t are perturbation-driving levels in equation (2), and ζ_t are the errors corresponding to slopes. κ_t, κ_t^* are the seasonal perturbations, with κ_t^* included by construction, just as in the case of γ_t^*, i.e. for the purpose of defining κ_t, and has no intrinsic importance. All perturbations are NID distributed with zero means and with Σ_ε, Σ_η, Σ_ζ, Σ_κ being the corresponding disturbance matrices.[1] Note that non-diagonal elements in these matrices provide useful information about correlations between unobserved components across countries.

In view of its similarity with Zellner's (1963) Seemingly Unrelated Equations (SURE) models, the family of multivariate STMs, including the Local Linear Trend model, are labeled as Seemingly Unrelated Time Series Equations (SUTSE) models. Just like SURE, these models take advantage of 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. In particular, perfect correlations between some of the perturbations can be interpreted as having certain of their components in common. This proposition may be elaborated more specifically as follows: the long-run correlations between the series are captured by the covariances of the off-diagonal elements in Σ_η. If, then, at least one of the correlations is equal to $|\ 1\ |$, this represents a case of common trends, and it is proved that the common non-stationary level can be removed by applying a linear combination of the series (Harvey, 1989, p. 451).

In fact, taking common factors into account constitutes a natural generalization of SUTSE models and, accordingly, the Local Linear Trend model presented above may be re-written as in Harvey (1993):

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[1] Assumptions made about the covariance matrix of (κ, κ) and (κ^*, κ^*) are usually imposed for reasons of parsimony and, also, for the model to be identifiable. See Harvey and Trimbur (2003b) for a detailed discussion of trigonometric cyclical models.

$$(4)\quad \pi_t = \Theta \cdot \mu_t^{+} + \mu^{*} + \gamma_t + \delta \cdot \omega_t + \varepsilon_t$$

$$(5)\quad \mu_t^{+} = \mu_{t-1}^{+} + \beta_{t-1} + \eta_t^{+}$$

$$(6)\quad \beta_t = \beta_{t-1} + \zeta_t$$

where the symbols have the same meaning and behaviour as in the case of the Local Linear Trend model, with the exception of μ_t^{+}, which is a Kx1 vector of common trends, μ^{*}, which is a vector of N constant elements with 0 in its first K elements and the last N-K elements are unconstrained, η_t^{+}, which is now distributed as $\eta_t^{+} \sim NID\left(0, \Sigma_{\eta^{+}\,KxK}\right)$, and Θ, which is an NxK matrix of factor loading (N≥K). This model is cointegrated of order (1,1), where the cointegrating vectors are the N-K rows of a matrix $A_{N-K,N}$ such as $A' \cdot \Theta = 0$, leading to $A \cdot \pi_t = A \cdot \mu^{*} + A \cdot \gamma_t + A \cdot \delta \cdot \omega_t + A \cdot \varepsilon_t$, in the *measurement equation*, where $A \cdot \pi_t$ is an (N-K)x1 stationary process. In this case, the resulting estimator can be expected to have a much smaller variance than the one constructed in the case of the univariate model.

In employing SUTSE models, a crucial property of the estimators of the intervention variable, is that efficiency gains are obtained. This proposition is demonstrated by Harvey (1996) in the case of the bivariate model with fixed trends, treating 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. The model employed is as in equation (7):

$$(7)\quad \begin{bmatrix} \pi_{1t} \\ \pi_{2t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \pi_{2t} + \delta \cdot \omega_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

where, again, the symbols are as above. We may note that $(\varepsilon_{1t}, \varepsilon_{2t})$ is normally distributed with zero mean, and $Var(\varepsilon_{1t}) = \sigma_1$; $Var(\varepsilon_{2t}) = \sigma_2$; both ε_{1t} and ε_{2t} perturbations are serially uncorrelated and $E(\varepsilon_{1t} \cdot \varepsilon_{2s}^{'}) = 0$ for t ≠ s. Furthermore, by applying a standard result on multivariate normal distribution (see, for example, Harvey, 1993, p. 103), equation (7) may be rewritten as:

$$(8)\quad \begin{bmatrix} \pi_{1t} \\ \pi_{2t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \theta \cdot \pi_{1t} + \mu^* + \delta \cdot \omega_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_t^* \end{bmatrix}$$

with $\theta = \rho_\varepsilon \cdot \sigma_2 / \sigma_1$, $\mu_t^* = \mu_{2t} - \theta \cdot \mu_{1t}$, $\varepsilon_t^* = \varepsilon_{2t} - \theta \cdot \varepsilon_{1t}$, where ρ_ε is the correlation between ε_{1t} and ε_{2t}. If θ is known then: $Var(\tilde{\delta}_{sutse}) = \sigma_2^2 \cdot (1 - \rho_\varepsilon)/T \cdot [\upsilon \cdot (1 - \upsilon)]$; *with* $\upsilon = (T - \tau + 1)/T$, where T is the number of observations.[2] Comparing this result with the corresponding one calculated when applying the univariate model, we may have: $Var(\tilde{\delta}_{univ}) = \sigma_2^2 / T \cdot [\upsilon \cdot (1 - \upsilon)]$ from which it is apparent that the variance estimated with SUTSE is lower by the factor $(1 - \rho_\varepsilon)$, which decreases the higher the correlation between the perturbations is.

[2] Note that, as Harvey (1996) poses it, "this expression [in our case equation 8] continues to hold approximately if θ is estimated" (p. 319; the expression in brackets is our addition).

Finally, the statistical application of STMs 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. Predictions can be derived by filtering forward, with the likelihood function based on innovations characterised by one-step-ahead predictions.

In the next sub-section we turn our attention to the form selected for modelling the intervention due to inflation targeting.

2.3 Intervention analysis

The intervention variable, ω_t, may be defined in the following different forms. First, outliers may be captured by means of pulse variables, which take the value of 1 at the point of intervention, occurring, say, at time t = τ, and 0 otherwise. Second, step variables can be used to identify a shift in the level of the series. These may be considered in the *measurement equation*, taking the value of 0 for the time periods previous to the intervention and 1 for all the following ones. The same model results from defining a pulse variable in the level equation, i.e. equation (2). Third, a change in the slope could be accounted for by postulating ω_t as null, up to the point of intervention, and then increase it gradually, such as, for instance, $\omega_t = t - \tau$ after the intervention period, which implies a change in the slope. Fourth, there is the possibility of defining a dynamic response to this intervention to account for effects that gradually die away. In this case, ω_t may, for instance, take the form:

$$\omega_t = \begin{cases} 0 \;\; if \quad t < \tau \\ \phi^{t-\tau} \;\; if \quad t \geq \tau \end{cases}$$

$$with \;\; 0 \leq \phi \leq 1$$

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). We utilize a step variable for the purposes of the current paper. This is clearly predicated on the reasonable assumption that the underlying level of the series presents a sustained change after the adoption of IT. 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 investigation.

We examine next the application of this approach in the case of the countries included in our sample as explained immediately below.

3. Empirical Evidence

In 1990, New Zealand was the first country to apply IT, when Government and Central Bank publicly announced their aim to achieve inflation levels of around 3-5% in the following year. Subsequently, a heterogeneous group of countries started to implement some form or another of this strategy in the 1990s and subsequently (Mishkin and Schmidt, 2001; Sterne, 2002). In order to analyze a relatively homogeneous group, the success of this approach is assessed in this paper on each country's headline CPI, by including in our sample only OECD countries: Australia, Canada, Finland, South Korea, New Zealand, Norway, Spain, Sweden, Switzerland and the United Kingdom. The United States (US) and the European Union (EU), two cases that do not pursue IT, are chosen as the control group, hence producing ten multivariate time-series models, one for each IT country, so that π_t is a vector of 3x1 (composed of the inflation at time t prevailing in the corresponding IT country, and also the inflation at time t in the two non-IT cases used as the control group). Our data series cover the period 1980(Q1) to 2004(Q4).

3.1 Empirical Evidence: Time Trend and Seasonality

We begin our discussion on the empirical evidence with the question of model selection, and in particular with the question of the type of the appropriate time trend and the existence of seasonality effects. We take the issue of the type of the time trend first.

The model we choose for μ_t is the most general Local Linear one as described above. This is subject to diagnostic checking which is reported and discussed in sub-section 3.2 (see, also, Table 3 below); the discussion therein supports this choice. It is also for the reason of wishing to employ a model, which is as general as possible, that we include slopes in all models tested in what follows.

Turning to the seasonality aspect, we note that inclusion of seasonality in our model is supported by visual inspection of the evidence presented in Figure 1, and by the more rigorously evidence-based results reported in Table 1. Figure 1 shows quarterly data of inflation levels for the case of IT and non-IT countries, US and the EU, over the period 1980(Q1) to 2004(Q4). 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 this 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. 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 all models is necessary. Almost all selected countries, with the exception of Australia and New Zealand, 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 all countries except for Finland and Spain for which it is 2.74). 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.

[FIGURE 1] [TABLE 1]

3.2 Empirical Evidence: Whole Model

A clear pattern of a downward trend in the inflation rates of the countries considered is evident from Figure 1. The question that arises, then, is the extent to which introduction of IT in the relevant countries can contribute in explaining this trend. The hypothesis adopted for the intervention analysis is that the introduction of IT induced a downward shift, once and for all. This can be captured by a step variable in the corresponding *measurement equation*, as explained in sub-section 2.3. Multivariate STMs are used to carry out intervention analysis with control groups. The inclusion of the latter is predicated on the reasonable 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. It is sensible, therefore, to expect common factors between IT and non-IT countries. In fact, as reported in Table 2, correlation coefficients between the inflation rates of the IT countries and non-IT countries included in our sample, are in most cases higher than 0.5. The correlation coefficients between US and New Zealand, as well as between US and Australia, constitute exceptional cases, with correlation coefficients around 0.3. As noted above, this methodology would contribute to obtaining a more precise assessment of the intervention effects, when all these series are considered in a multivariate model.[3]

In Table 3, we report the main summary statistics, designed to diagnose the performance of the model as depicted in equations (4) to (6), and estimated for the full sample.[4] We also report in the same table and under 'Component', the variances of the disturbances that drive the different components for all series in the models, called in the literature the hyperparameters (Harvey, 1989). The main summary statistics are presented in the first part of each country's reported table. H(h) is a test for heteroscedasticity, and it is distributed approximately as F(h,h), where h is equal to 31 in all countries, except for Finland and Spain for which h = 23; 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

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[3] While considering a slope is more debatable, it is, nonetheless, included in all models, which enables us to start with the most general Local Linear Trend model.

[4] All estimations were run using STAMP as in Koopman et al. (1999).

based on the first P residual autocorrelations and distributed approximately as χ^2 with d degrees of freedom, where d is equal to (P + 1) minus the number of estimated parameters; seasonality is tested utilizing a χ^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). In the second part of each country's table, labeled as 'Components', the estimated hyperparameters are reported. The mnemonics are as follows: Irr stands for 'irregulars', and estimates the variance of pertubations in the measurement equation ($\tilde{\sigma}^2_{\varepsilon_{it}}$); Lvl corresponds to the variance of the perturbations driving levels ($\tilde{\sigma}^2_{\eta_{it}}$); Slp accounts for the estimation of the variance of errors corresponding to slopes ($\tilde{\sigma}^2_{\zeta_{it}}$ ζ_t); and Sea stands for the estimated variance of the seasonal perturbations ($\tilde{\sigma}^2_{\kappa_{it}} = \tilde{\sigma}^2_{\kappa^*_{it}}$).

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 all cases, with the exception of the UK, so neither is there a problem of autocorrelation. The seasonality statistic rejects the absence of seasonality patterns in the control-group case at the 10% level of significance. The same occurs in five IT cases (Canada, Finland, Norway, South Korea and Switzerland), which suggests that accounting for the seasonal components in all models is very pertinent. All R^2s appear to be reasonable. Note that almost all components are different from zero, with the exception of Canada in the case of the level (labeled as ‘Lvl’), thereby confirming satisfactory model selection. Where the hypothesis is rejected (levels in the Canadian model), the model was replicated with a fixed (i.e. non-stochastic) trend with very similar results.

[TABLE 2] [TABLE 3]

3.3 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 δ 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 commom factors are evident in the multivariate model. The last column reports the RMSEs corresponding to the model in its univariate form. We include the RMSE for both the multivariate and univariate case for comparative purposes. In the univariate case RMSEs are calculated by including only the IT countries, without the control group, along with the intervention variable. We may note that all RMSEs obtained for the parameters corresponding to the intervention analysis are higher in the univariate applications than the ones obtained by operating on the multivariate STM common factor models. This supports the contention that multivariate STM estimations are more efficient than univariate

STM estimations. Note that with one exception (Sweden) all of the IT countries present at least one common trend (labeled as 'CFT'). In three of the countries the models are estimated with common slopes (labeled as 'CFSL') and in one case the model is estimated with common seasonal factors (labeled as 'CFSE').

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 three cases the coefficient is positive but insignificant. It is apparent that only in the cases of Canada and South Korea, was the intervention coefficient significant at the 5% level. These results produce, in the case of Canada a one and for all decrease of 0.5% per quarter in the underlying inflation level of the series, and a decrease of almost 1% in the case of South Korea. In Figure 2 the dates of IT imposition are recorded along with the point of intervention, indicated with a vertical bar. Clearly, Canada and South Korea achieved a significant reduction in their stochastic trends at the time of intervention. This is especially noticeable when compared with the control group, which shows a smooth on-going trend at each point of intervention. Interestingly enough, only 3 other countries present p-values under the level of 0.30. These are Sweden, Switzerland and the UK, for which slightly lower coefficients are obtained, though non-significant at the 10% level of statistical significance. As expected for these cases, the estimates obtained show a small change in the underlying trend. The rest of the IT countries can be grouped in two categories. Australia, Norway and Spain where the intervention coefficient is positive but insignificant, suggesting that IT may have had a perverse effect. It is true, though, that after a while inflation does decrease in all these three cases. This may be interpreted as the result of the time lag in the impact of monetary policy, which may very well be longer than in the case of the other countries. The other category includes Finland and New Zealand where the downward trend in inflation commences before the IT imposition. So that when IT was introduced inflation had already been tamed.

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 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; and Petursson, 2004, is a representative sample) 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.

[TABLE 4] AND [FIGURES 2.1 – 2.10]

3.4 Empirical Evidence: The 'Lock-In' Effect

We begin by testing for the differences in the inflation variances that correspond to two periods: 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 country. Variances are significantly different for both periods in all countries implementing IT at the 10% level of significance, and most of them are significantly different at the 5% level. Similar 'lock-in' results, however, are evident in the case of the non-IT countries in relation to the tests implemented in this section. Superficially the results in this table would support the hypothesis of significant 'lock-in' effects. Surely, though, further and more robust tests are required.

In the rest of this section we test further for the possibility of 'lock-in' effects by employing STM methods. SUTSE models are estimated for the vector π_t and for the period prior to intervention (t=1,…, τ-1). Then, one-step ahead predictions are undertaken for t= τ+1,…,T, and these are compared with the actual values of inflation. As a result of this procedure, standardized one step-ahead prediction errors $(\tilde{\nu}_t)$[5] are computed and, subsequently, graphical procedures and statistical tests are employed to examine the possibility of 'lock-in' effects.

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[5] $\tilde{\nu}_t = \nu_t / f_t^{1/2}$, where ν_t is the one-step ahead prediction error and f_t is the estimate of its variance (Harvey, 1989, pp. 289).

We provide CUSUM plots in Figure 3. These depict an initial impression of how inflation evolved after intervention. The following formula is utilized to construct these plots:

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

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.

The CUSUM plots in Figure 3 refer to all IT countries in our sample. 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 has an 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 negative, but none of them crosses the significance lines and all plots tend to revert to a zero mean. This is evidence, which can be interpreted as successful implementation of monetary policies in preventing inflation from bouncing back to previously registered high values, or even to lower values 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 the result of formal statistical tests are reported. CUSUM t-tests are applied to the 10 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:

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

which is distributed as a t-statistic with (T-τ) degrees of freedom. 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 examine whether 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. 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, i.e. 1.96, at the 5% level of significance. The same results are evident in the case of the control group as well. As reported in the relevant columns for the European Union and the United States in Table 6, this occurs to all cases and, therefore, for all dates for which IT was implemented. The computed CUSUM t-values are well below their critical values in all countries.

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 10 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.[6] Which these factors might be are beyond the scope of this paper.

[TABLES 4 AND 5] AND [FIGURE 3]

4. Summary and conclusions

In this paper we have attempted to produce empirical evidence in the case of a number of OECD countries, applying Intervention Analysis to multivariate STMs. Although we have suggested at the outset that the existing overall empirical evidence on IT is mixed, the prevailing view is that IT has gone hand-in hand with low inflation (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 produced evidence that suggests that non-IT central banks have also been successful in achieving and maintaining consistently low inflation rates. It follows then that this evidence would suggest that a central bank does not need to pursue an IT strategy to achieve and maintain low inflation. It would, thus, appear that Mishkin’s (1999) statement that the reduction of inflation in IT countries “beyond that

[6] It is interesting to note that Ball and Sheridan (2003) reach a similar conclusion utilising a completely different approach and technique.

which would likely have occurred in the absence of inflation targets" (p. 595) is not supported by the available empirical evidence; as such that statement was highly premature.

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TABLES AND FIGURES

Figure 1. Inflation (% change in CPI)

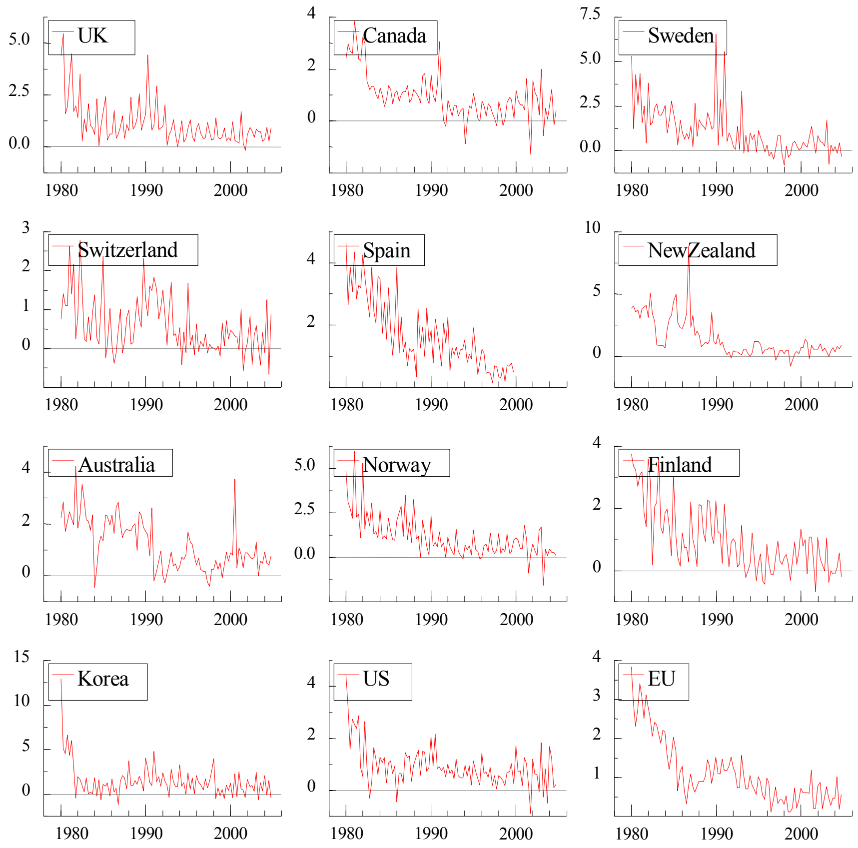
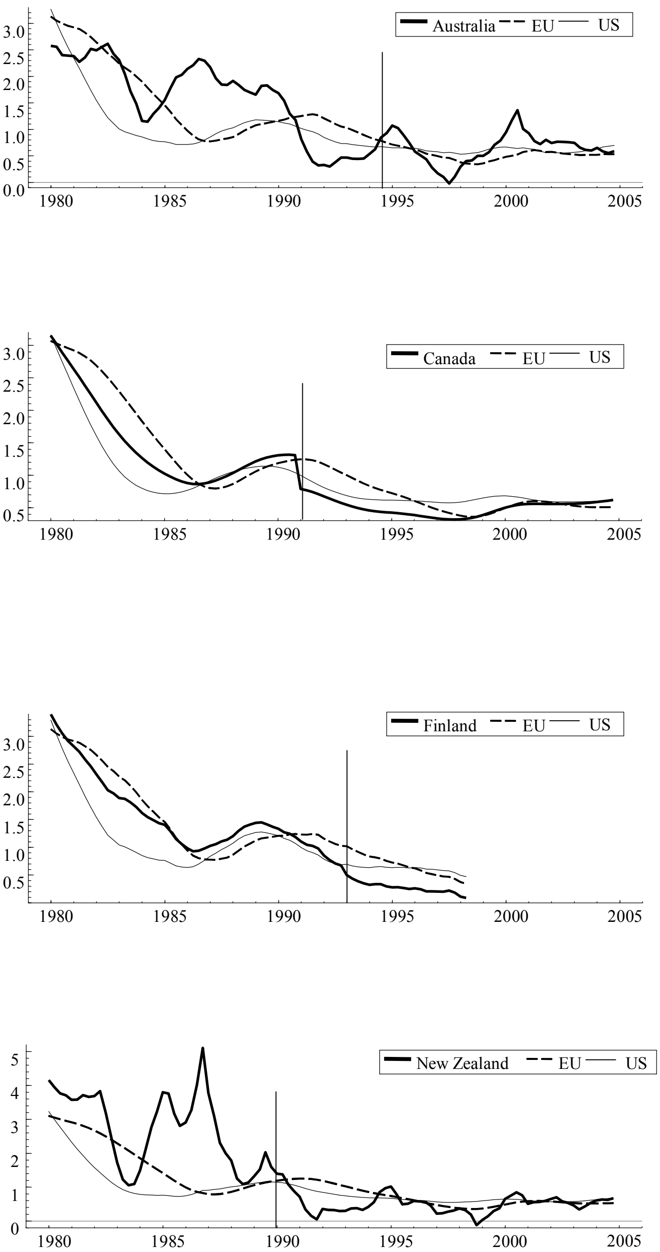
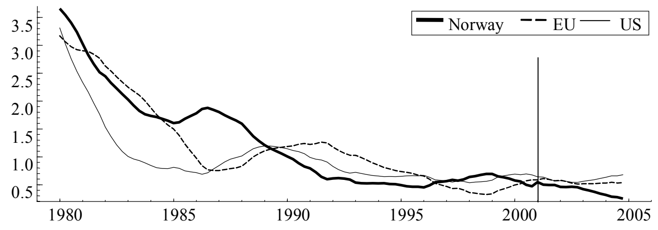
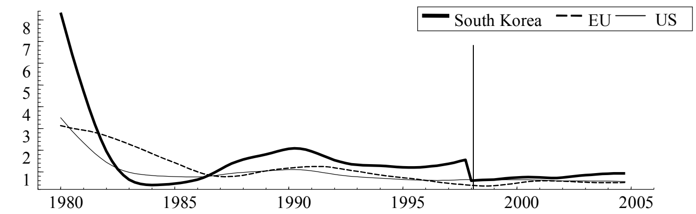
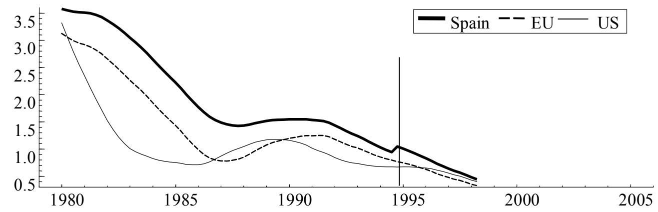


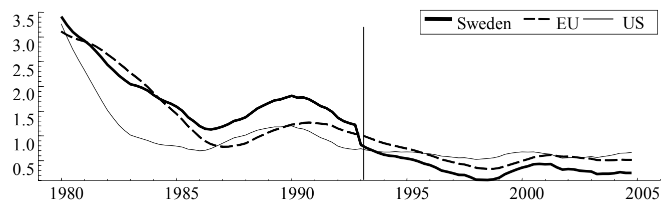
Figure 2. Trends and interventions in IT and non-IT countries (%)

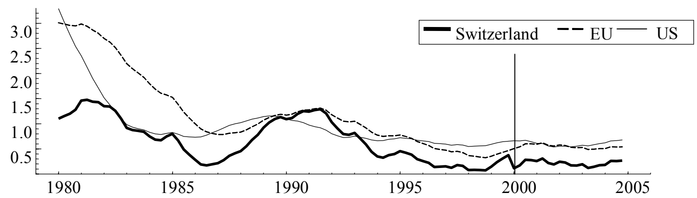



Norway
EU
US
3.5
3.0
2.5
2.0
1.5
1.0
0.5
1980
1985
1990
1995
2000
2005


South Korea
EU
US
8
7
6
5
4
3
2
1
1980
1985
1990
1995
2000
2005


Spain
EU
US
3.5
3.0
2.5
2.0
1.5
1.0
0.5
1980
1985
1990
1995
2000
2005


Sweden
EU
US
3.5
3.0
2.5
2.0
1.5
1.0
0.5
1980
1985
1990
1995
2000
2005


Switzerland
EU
US
3.0
2.5
2.0
1.5
1.0
0.5
1980
1985
1990
1995
2000
2005

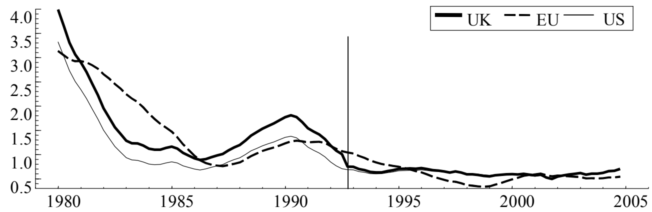

UK
EU
US
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
1980
1985
1990
1995
2000
2005

Figure 3. Plot of CUSUM standardized residuals

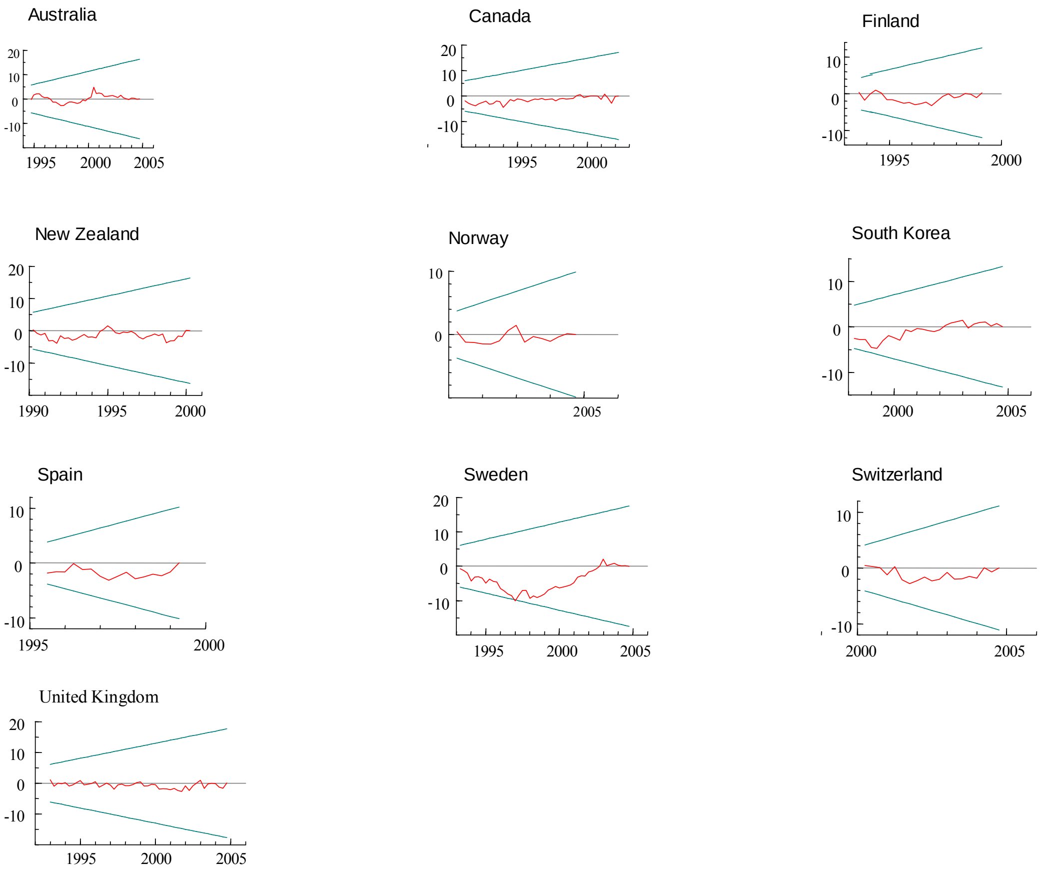


Table 1. Significance of seasonal dummies

	Q1+	Q2	t-statistic++	Q3	t-statistic++	Q4	t-statistic++	Obs.	R^2	F(3,T-3)
Australia	-0.279	0.026	(0.15)	0.152	(0.86)	0.101	(0.57)	99	0.01	0.37
Canada	0.721	-0.264	(1.76)	-0.4	(2.67)**	-0.057	(0.38)	99	0.10	3.47**
Finland	2.311	-1.651	(4.92)**	0.283	(0.84)	-0.943	(2.81)**	79	0.18	5.63*
New Zealand	-0.384	0.38	(1.71)	-0.076	(0.34)	0.08	'(0.36)	99	0.03	1.06
Norway	1.52	-1.244	(5.43)**	0.044	(0.19)	-0.32	(1.40)	99	0.25	10.50*
South Korea	1.165	-0.235	(1.17)	-0.776	(3.86)**	-0.154	(0.77)	99	0.25	10.95*
Spain	0.774	-0.986	(5.58)**	0.5	(2.83)**	-0.288	(1.63)	79	0.35	13.93*
Sweden	1.281	-1.233	(4.16)**	0.445	(1.50)	-0.493	(1.66)	99	0.19	7.43*
Switzerland	0.337	-0.373	(2.24)*	-0.181	(1.08)	0.217	(1.31)	99	0.08	2.63
UK	0.329	1.022	(7.50)**	-1.436	(10.53)**	0.085	(0.62)	99	0.64	55.83*
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:

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

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

	European Union	United States
Australia	0.53	0.27
Canada	0.77	0.62
Finland+	0.77	0.65
New Zealand	0.47	0.33
Norway	0.66	0.52
South Korea	0.49	0.71
Spain+	0.84	0.48
Sweden	0.59	0.51
Switzerland	0.52	0.49
UK	0.61	0.66

Notes:

+ The time span for these countries is 1980(Q1)-1998(Q2).

Table 3. Summary statistics for the models estimated for the full sample

	EU	US	Australia
H(31)	0.78022	0.38654	0.91779
DW	1.8396	2.0177	2.0777
Q(9,6)	10.29	6.1444	5.9673
Seasonality	18.45**	44.99**	2.04
Rs^2	0.28499	0.42333	0.33351
Component			
Irr	0.035864	0.21374	0.29613
Lvl	0.002381	0.002263	0.066322
Slp	0.000319	0.000642	7.11E-05
Sea	0.00019	0.000689	0.000456

	EU	US	Canada
H(31)	0.7322	0.41095	1.832
DW	1.8497	1.9749	1.7062
Q(9,6)	10.031	4.3251	8.4661
Seasonality	20.23**	34.38**	35.31**
Rs^2	0.2935	0.42918	0.33052
Component			
Irr	0.03816	0.22543	0.26513
Lvl	0	0	0
Slp	0.000415	0.000546	0.000306
Sea	0.000188	0.000671	4.78E-05

	EU	US	Finland
H(23)	0.7723	0.11291	0.37578
DW	1.8177	2.0313	2.3054
Q(9,6)	7.9046	6.8026	4.3715
Seasonality	15.32**	6.85*	30.77**
Rs^2	0.1464	0.34228	0.45396
Component			
Irr	0.035476	0.2263	0.22348
Lvl	0.003459	0.002654	0.010901
Slp	0.00034	0.000926	0.00024
Sea	0.00017	0.000634	0.000355

	EU	US	New Zealand
H(31)	0.72191	0.38046	0.09022
DW	1.8353	1.9825	1.9585
Q(9,6)	9.419	5.2527	9.4924
Seasonality	17.67**	31.65**	1.43
Rs^2	0.27244	0.40419	0.15651
Component			
Irr	0.037656	0.21996	0.43684
Lvl	3.09E-05	0.000233	0.29128
Slp	0.000412	0.000624	0.00077
Sea	0.000201	0.000733	0.0002

	EU	US	Norway
H(31)	0.74569	0.36518	0.73103
DW	1.8902	2.0126	2.0577
Q(9,6)	10.979	6.1745	3.6333
Seasonality	19.80**	41.55**	6.95*
Rs^2	0.3021	0.4379	0.53959
Component			
Irr	0.03294	0.21054	0.26019
Lvl	0.004956	0.004471	0.005437
Slp	0.000213	0.000593	0.000281
Sea	0.000219	0.000733	0.002051

	EU	US	South Korea
H(31)	0.70406	0.42308	0.35353
DW	1.7913	2.0101	1.5033
Q(9,6)	9.9965	5.3027	11.449
Seasonality	20.49**	31.14**	53.23**
Rs^2	0.29517	0.5007	0.31068
Component			
Irr	0.036931	0.21206	0.9112
Lvl	0.000719	0.00035	0.001645
Slp	0.000354	0.000707	0.007695
Sea	0.000201	0.000763	0.000336

	EU	US	Spain
H(23)	0.73764	0.099716	0.40306
DW	1.7552	1.9903	2.2334
Q(9,6)	6.8144	5.9274	14.205
Seasonality	16.06**	8.85*	0.54
Rs^2	0.13333	0.32758	0.52371
Component			
Irr	0.036398	0.23119	0.19152
Lvl	0.001674	0.001735	0.000594
Slp	0.00041	0.000914	0.000344
Sea	0.000205	0.000581	0.002636

	EU	US	Sweden
H(31)	0.6974	0.39543	0.54224
DW	1.8438	2.0613	2.4153
Q(9,6)	10.602	5.671	16.752
Seasonality	21.74**	36.94**	1.96
Rs^2	0.2981	0.41899	0.57177
Component			
Irr	0.037218	0.2176	0.69478
Lvl	0.001964	0.005922	0.014171
Slp	0.000317	0.000524	0.000119
Sea	0.000161	0.000616	0.001874

	EU	US	Switzerland
H(31)	0.66693	0.41231	0.28787
DW	1.8428	2.0754	1.9181
Q(9,6)	9.4764	6.8999	5.7541
Seasonality	20.99**	45.13**	10.28**
Rs^2	0.30655	0.43058	0.48714
Component			
Irr	0.034311	0.21731	0.19009
Lvl	0.00542	0.002814	0.021233
Slp	0.000202	0.000661	0.000121
Sea	0.0002	0.000869	0.004851

	EU	US	UK
H(31)	0.7616	0.46564	0.44931
DW	1.8833	1.9718	2.0544
Q(9,6)	9.7154	6.5422	21.53
Seasonality	20.41**	32.27**	3.36
Rs^2	0.27923	0.47714	0.40184
Component			
Irr	0.03866	0.22229	0.17871
Lvl	0.002267	0.003401	0.006243
Slp	0.000313	0.000674	0.000893
Sea	0.000121	0.000405	0.000681

Notes:

* Null of non-seasonality rejected at 1%;

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

Table 4. Intervention Estimates

	Dates of Intervention	Multivariate STM estimates Coefficient	RMSE	t-value	p-value	Common Factors	Univariate RMSE
Australia	1994/Q3	0.243	0.524	0.4634	[0.6441]	1CFT	0.557
Canada	1991/Q1	-0.507	0.212	-2.3947	[0.0186]	2CFT	0.442
Finland	1993/Q1	-0.186	0.290	-0.6420	[0.5230]	2CFT	0.409
New Zealand	1990/Q1	-0.140	0.892	-0.1569	[0.8757]	1CFT	0.912
Norway	2001/Q1	0.090	0.337	0.2672	[0.7899]	2CFT, 1CFSL	0.409
South Korea	1998/Q1	-0.994	0.497	-1.9995	[0.0484]	2CFT, 1CFSL	0.906
Spain	1994/Q4	0.148	0.173	0.8531	[0.3966]	2CFT	0.355
Sweden	1993/Q1	-0.410	0.393	-1.0426	[0.2998]	1CFSE	0.598
Switzerland	2000/Q1	-0.338	0.284	-1.1908	[0.2367]	2CFT	0.395
United Kingdom	1992/Q4	-0.235	0.200	-1.1763	[0.2424]	2CFT, 1CFSL	0.375

Notes:

The period of estimation is 1980(Q1)-2004(Q4) for all countries with the exception of Finland and Spain for which it is: 1980(Q1)-1998(Q2).

Table 5. Variances in pre-IT and post-IT periods

	IT Country		European Union		United States	
	Pre-IT	**Post-IT**	**Pre-IT**	**Post-IT**	**Pre-IT**	**Post-IT**
Australia	0.980	0.409*	0.657	0.077*	0.744	0.325*
Canada	0.682	0.443***	0.749	0.132*	0.894	0.259*
Finland+	1.101	0.241*	0.683	0.108*	0.798	0.121*
New Zealand	2.561	0.197*	0.804	0.151*	0.941	0.314*
Norway	1.398	0.761***	0.693	0.095*	0.618	0.617
South Korea	4.071	1.268*	0.678	0.078*	0.670	0.419***
Spain +	1.179	0.212*	0.658	0.072*	0.137	0.732*
Sweden	1.977	0.469*	0.683	0.102*	0.798	0.295*
Switzerland	0.531	0.280**	0.710	0.077*	0.632	0.565
UK	1.457	0.161*	0.681	0.100*	0.841	0.276*

Notes:

* 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.
\+ The time span for these countries is 1980(Q1)-1998(Q2).

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

	IT Country	European Union	United States	Degrees of freedom
Australia	0.730	0.441	-0.102	41
Canada	-0.547	0.058	-0.179	55
Finland +	1.120	-0.204	-0.124	23
New Zealand	0.365	0.669	-0.200	59
Norway	-0.838	-0.474	-0.001	15
South Korea	-0.902	-0.307	1.633	27
Spain +	-0.042	-0.004	-0.074	16
Sweden	-0.137	0.069	0.027	47
Switzerland	-0.252	0.043	-0.294	19
UK	0.008	1.219	1.353	48

Notes:

No failures detected at the 5% significant level with 1.96 critical value.

\+ The time span for these countries is 1980(Q1)-1998(Q2).