Asymmetric Behaviour of Inflation around the Target in Inflation-Targeting Countries

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Abstract: *We explore the asymmetric behaviour of inflation around the target level for inflation-targeting countries. The first rationale behind this asymmetry is the asymmetric policy response of the central bank around the target. Second rationale is the asymmetric inflation persistence. We suggest that recently developed Asymmetric Exponential Smooth Transition Autoregressive (AESTAR) model provides a convenient framework to capture the asymmetric behaviour of inflation driven by these two effects. We further conduct an out-of-sample forecasting exercise and show that the predictive power of AESTAR model for inflation is high for some countries in our sample, especially at long-horizons.*

JEL Classification: C32, E37

Keywords: Inflation, forecasting, nonlinear adjustment.

Central banks of numerous developed countries and emerging markets adopted inflation-targeting (IT) regime in the last two decades. The forward-looking nature of the IT regime calls for a rich information set of robust indicators and reliable inflation forecasts for policymakers. Accordingly, many inflation-targeting central banks aim to improve their forecasting ability through employing alternative approaches including econometric models as well as expert judgements[1]. This paper contributes to this literature by showing that the recently developed Asymmetric Exponential Smooth Transition Autoregressive (AESTAR)

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[1] See Andersson and Löf (2007) for Riksbank, Kapetanios et al. (2008) for Bank of England, Bjørnland et al. (2008) for Norges Bank and Ogunc et al. (2013) for Central Bank of the Republic of Turkey.

model (Sollis, 2009) can capture the asymmetric behaviour of inflation against deviations from a pre-determined target level in an IT framework. Conducting an empirical analysis covering nineteen IT countries, we further show that the performance of this model for predicting inflation is high, especially at long-horizons, for some countries in our sample.

The asymmetric behaviour of inflation captured by AESTAR model is explicated by two rationales affecting the adjustment towards policy target. First one is the asymmetric response of the policymaker against upwards or downwards deviations of inflation from a pre-determined target level (or band) in an IT framework. Second one is the asymmetry in the persistence of shocks to the inflation process. We argue that the cross-country differences among the degree of asymmetry and adjustment process in our set of inflation-targeting countries could be explained by the relative strength of these two drives. This introductory section provides further motivation for these two different types of asymmetries. The second section introduces the econometric methodology built on these premises and presents a brief literature review.

The first motivation above; the asymmetric monetary policy response against departures from the policy target, is based on two conjectures, as follows. First, as Orphanides and Wieland (2000) argue, many inflation-targeting central banks aim to keep inflation within a target range rather than focusing on a point target. Consequently, the policy response function of the central bank shows a nonlinear behaviour depending on inflation being inside or outside of a specific zone:

"*As a consequence, if the policymaker assigns at least some weight to output stabilization, the output objective will dominate at times when inflation is within the zone but will recede in importance when inflation is outside the zone."* (Orphanides and Wieland, 2000).

According to this view when the deviation in inflation from the target level is *above or below* a certain threshold, central bank takes necessary actions to take the inflation back to the target level[2]. As will be detailed in the second section, Exponential Smooth Transition Autoregressive (ESTAR) model provides a suitable framework for modelling this kind of a response structure.

Our second conjecture is that, in addition to this kind of threshold behaviour, there is a further asymmetry in monetary policy response of central banks against deviations of inflation from a pre-defined target level. Policymakers in inflation-targeting countries could be more *biased* against *upwards* jumps in inflation rather than downwards movements. As the argument goes, undershooting the inflation target does not affect the credibility of the inflation-targeting central bank as much as overshooting. Moreover, the tendency of central bank to focus on other objectives than inflation could be stronger when inflation rate stays below the target level. Accordingly, the monetary policy response would be more immediate and strong in case of a positive deviation from the target level rather than its negative equivalent, provided that the deviation is above a certain threshold[3].

The second motivation behind the asymmetric behaviour in inflation is a possible asymmetry in the persistence of shocks to the inflation process. Positive deviations of inflation from a target level could be larger and more persistent compared to downwards movements. Recently, a number of studies that employ quantile-regression methods introduced by Koenker and Xiao (2004, 2006) suggest that the mean-reverting process of inflation towards a long-run equilibrium could be affected by the size and the sign of the shock. In particular, Tsong and Lee (2011) examines the mean-reversion in inflation in 12 OECD countries and show that the adjustment towards the long-run mean is stronger for negative shocks to inflation compared to the positive ones. Recently, Tillmann and Wolters (2012) and Manzan and Zerom (2014) find similar results for US inflation[4]. Our paper

[2] Parkin (2013) argues that an important factor that could determine the central bank's stance on the tradeoff between inflation volatiliy and output volatility within an inflation targeting framework is the level of central bank independence.

[3] Obviously, one would argue that a negative deviation should also raise concerns for deflation spiral for a central bank. However, the historically high inflation rates in many countries led to a perception in public mind that inflation would not go down as easily as it goes up.

[4] Inflation persistence could also be related with the level of inflation. A positive relationship between the two could be a result of gradual adjustment of inflation expectations to the central bank's target due to imperfect credibility of the monetary authority, which increases the cost of disinflation (Erceg and Levin, 2003). However, the evidence on the effect of adoption of an inflation targeting regime on persistence of inflation is somewhat mixed. Levin, Natalucci, and Piger (2004) documents lower persistence of inflation after implentation of IT regimes for a number of industrial countries. Siklos (2008) shows that only four out of thirteen emerging market inflation targeters displayed a decline in inflation persistence after adoption of IT regime. Gerlach and Tillmann (2012) also confirms this result for some Asian countries

suggests that the recently proposed AESTAR model provides a convenient framework to capture the asymmetric inflation behaviour which includes these two effects.

The approach pursued in this study is connected with two recently developing strands of literature. First, non-linear models are frequently employed to analyse the mean-reverting behaviour of different macroeconomic variables recently. Moreover, these models have also been valuable in inflation forecasting practices. Second, our conjecture above is in line with the recent literature that points out a departure from the well-known linear-quadratic approach that assumes a quadratic loss function and a corresponding linear policy rule for central banks. We summarize these two avenues of literature in the next section by a focus on the treatment of loss-function of central banks on the theoretical side and a focus on self-exciting threshold models on the empirical side.

The third section follows the steps of nonlinear model building as described in Teräsvirta (2006). At first, linearity tests are conducted along with the unit root and structural break tests. Linearity testing is an important pre-requisite of building smooth transition models since these models nests a linear regression model which would be unidentified in case of a linear data generating process. Accordingly, we conduct ESTAR and AESTAR unit root tests among nineteen inflation-targeting countries in our sample. After detecting non-linearities in inflation series for eight of these countries, we estimate the corresponding nonlinear models and report the set of parameters that determine the degree of asymmetry and the speed of adjustment.

In the fourth section, we conduct an out-of-sample forecasting exercise for these eight countries where we show that the predictive power of our nonlinear models are better than that of a benchmark random walk model for some countries, especially at long-horizons. This result corroborates with some recent studies in the literature which points out high performance of nonlinear models in forecasting macroeconomic variables in the long-run.

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that implements IT. Recently, Manzan and Zerom (2014) suggesst that the asymmetric persistence of inflation shocks in US could be explained with the positive relationship between the level of inflation and its volatility.

Fifth and the last section will conclude. We believe that our results would be useful for researchers and in particular central bankers in search of accurate inflation forecasts.

I. Literature Review and Econometric Methodology

Nonlinear models are widely adopted in the recent literature in order to capture the asymmetric behaviour of several macroeconomic variables. A broad classification of these models can be based on the presumed regime-switching behaviour of the series. Markov-switching models contain transition probabilities described by a Markov-chain process under the assumption that the regime change is determined by an unobservable variable. Alternatively, threshold models assume that the shift from one regime to another is determined by an observable variable. In particular, self-exciting threshold models assume that the regime switching behaviour is determined by the past values of the time series under consideration.

Recent non-linear modelling literature reveals prevalence of self-exciting threshold models such as Threshold Autoregressive (TAR) or Smooth Transition Autoregressive (STAR) models. Among these two types, TAR models assume an immediate transition to a long-run level, once the series crosses a certain threshold (Tong, 1990). Alternatively, STAR type models suggest a gradual or smooth adjustment to the mean (Granger and Teräsvirta, 1993).

A popular extension of STAR models is the ESTAR model (Kapetanios et al., 2003), which assumes a *symmetric* and gradual adjustment. This approach provides us a convenient framework to capture the inflation behaviour in an IT regime. As the argument goes, policymakers respond to deviations in inflation from the target level, only if these deviations are beyond a certain threshold.

This aforementioned nonlinear response of monetary policy points out a departure from the traditional linear-quadratic approach that describes the behaviour of central banks with inflation and output objectives. This well-established line of literature assumes a quadratic loss function for central bank with a linear aggregate supply constraint which in turn leads to a linear monetary policy rule (Svensson, 1997, and Clarida et al.,1999). This view is questioned by many studies in the recent literature[5]. For example, Orphanides and Wieland (2000) argue that many inflation-targeting central banks aim to keep inflation within a target range rather than focusing on a point target[6]. They point out *nonlinearity in the policy response function* which is determined by the inflation being inside or outside a specific zone. ESTAR model provides an appropriate representation of this view. Once the inflation is *above* or *below* the inflation target to a certain extent, then the central bank would respond and the inflation would come back to the target level in a *gradual* manner. Kapetanios et al. (2008) apply this model as a part of their inflation forecasting exercise for Bank of England (BOE) and documents good forecasting performance of ESTAR model for UK inflation[7,8].

The formal model in Kapetanios et.al (2003) can be written as:

$$\Delta\pi_t = a_1\pi_{t-1} + a_2\pi_{t-1}\left[1-\exp(-\theta(\pi_{t-d}-\lambda)^2)\right]+\varepsilon_t \qquad (1)$$

The transition function inside the brackets includes the coefficient of the speed of adjustment, θ which determines the smoothness of the transition between the regimes. Similar to Kapetanios et.al (2003) we impose a mean-zero stochastic process, setting $\lambda = 0$ and further choose $a_1 = 0$ assuming that the series display unit root behaviour when it is close to its long-run value, yet shows mean-reverting behaviour when it is far away from it. Selecting the delay parameter as $d = 1$, we obtain:

$$\Delta\pi_t = a_2\pi_{t-1}\left[1-\exp(-\theta\pi^2_{t-1})\right]+\varepsilon_t \qquad (2)$$

As argued in Teräsvirta (2005) the first step in nonlinear model building is linearity testing. In equation (2) above the null hypothesis is $H_0 : \theta = 0$ against the alternative $H_1 : \theta > 0$. However, a common problem in these type of models is that the parameter (a_2) is

[5] For a review of this literature see Dolado et al. (2004).
[6] Also, see Orphanides and Wilcox (2002), Aksoy et al. (2006) and Martin and Milas (2010) for a discussion of the opportunistic approach to disinflation.
[7] The policy mandate of Bank of England (BOE) is keeping inflation at 2 %. ESTAR model assume that if the deviation in inflation from this target level is high enough (in either way) then BOE conduct policies to bring inflation back to the %2 target level.
[8] Lundberg and Teräsvirta (2006) also develops smooth transition autoregressive model to examine the target zone behavior of exchange rates for Sweden and Norway.

unidentified under the null. To address this problem, Kapetanios et.al (2003) suggest an auxiliary regression, using a first order Taylor series approximation. The general model including serially correlated errors then reads:

$$\Delta\pi_t = \sum_{j=1}^{p} p_j \Delta\pi_{t-j} + \gamma\pi_{t-1}{}^{3} + error \qquad (3)$$

The asymptotic critical values for the t-statistics by employing the OLS estimation of $\gamma(\hat{\gamma})$ are given in Kapetanios et.al (2003)[9].

A recent extension ESTAR type of modelling is proposed by Sollis (2009) as the AESTAR model. The adjustment is gradual again but this time, an *asymmetric* response is allowed for the policymaker. As explained in the introductory section of our paper, the policy response of the central bank could be stronger and more immediate against overshooting the target rather than undershooting, provided that the deviation from the inflation target is above a certain threshold.

This aforementioned view also follows the same lines with the literature that confronts the linear-quadratic paradigm. Martin and Milas (2004) examine the UK monetary policy after the adoption of inflation targeting in 1992. Using a quadratic logistic function they assign different weights to regimes which define different Taylor-like policy rules. The width of the band, inside which inflation can deviate from the target level, is different in both regimes. Using nonlinear policy rules they show that BOE aimed to contain inflation within a target zone rather than a point target during these years, as suggested by Orphanides and Wieland (2000) above. Their results further support our central hypothesis. They argue that monetary policy response by BOE in this period is asymmetric in the sense that the policy response is stronger against positive deviations from the target rather than negative deviations.

Ruge-Murcia (2003) develops a game-theoretic model where central bank is allowed to assign different weights to deviations in their loss function, depending on the deviations being above or below the target. His empirical analysis also provides supporting evidence for

[9] Aksoy and Leon-Ledesma (2008) applies TAR and ESTAR tests for 249 macroeconomic series of the G7 countries. Their results suggest a higher frequency of rejection of the null of a unit root as compared to the linear unit root tests.

such asymmetric preferences for Canada, Sweden and UK. Dolado et al. (2004) also reports evidence for asymmetric inflation preferences for US FED after 1983.

To capture such asymmetric policy response we demonstrate AESTAR model below. Sollis (2009) extend the Kapetanios et al. (2003) model in a way to allow for asymmetric nonlinear adjustment:

$$\Delta\pi_t = G(\theta_1, \pi_{t-1})[S(\theta_2, \pi_{t-1})a_1 + \{1 - S(\theta_2, \pi_{t-1})\}a_2]\pi_{t-1} + \varepsilon_t \qquad (4)$$

where

$$G(\theta_1, \pi_{t-d}) = 1 - \exp(-\theta_1 \pi^2{}_{t-1}), \quad \theta_1 > 0 \qquad (5)$$

$$S(\theta_2, \pi_{t-d}) = [1 + \exp(-\theta_2 \pi_{t-1})]^{-1}, \quad \theta_2 > 0 \qquad (6)$$

In equation 4, assuming without loss of generality $\theta_1 > 0$ and $\theta_2 \rightarrow \infty$, if π_{t-1} moves from 0 to -∞ then $S(\theta_2, \pi_{t-d}) \rightarrow 0$ and ESTAR transition occurs between the central regime model $\Delta\pi_t = \varepsilon_t$ and the outer regime model $\Delta\pi_t = a_2\pi_{t-1} + \varepsilon_t$ where speed of transition is determined by θ_1. Similarly, if π_{t-1} moves from 0 to ∞ then $S(\theta_2, \pi_{t-d}) \rightarrow 1$ and ESTAR transition occurs between the central regime model $\Delta\pi_t = \varepsilon_t$ and the outer regime model $\Delta\pi_t = a_1\pi_{t-1} + \varepsilon_t$ where speed of transition is determined by θ_1. Asymmetric response is maintained by $a_1 \neq a_2$. The model is generalized to account for serially correlated errors as:

$$\Delta\pi_t = G(\theta_1, \pi_{t-1})[S(\theta_2, \pi_{t-1})a_1 + \{1 - S(\theta_2, \pi_{t-1})\}a_2]\pi_{t-1} + \sum_{i=1}^{k} \kappa_i \Delta\pi_{t-i} + \varepsilon_t \qquad (7)$$

Once the unit root testing is concerned, the same identification problem with the ESTAR case is present. To overcome this problem in a similar fashion to Kapetanios et al. (2003), Sollis (2009) recommends a two-step Taylor series expansions; first around θ_1 and then around θ_2 where the resulting model is:

$$\Delta\pi_t = \phi_1(\pi_{t-1})^3 + \phi_2(\pi_{t-1})^4 + \sum_{i=1}^{k}\kappa_i\Delta\pi_{t-i} + \mu_t \quad (8)$$

with $\phi_1 = a_2^{*}\,\theta_1$ and $\phi_2 = \mathrm{c}\left(a_2^{*} - a_1^{*}\right)\theta_1\theta_2$ where c=0.25, a_1^{*} and a_2^{*} are functions of a_1 and a_2 as described in Sollis (2009). The null hypothesis is:

H_0: $\phi_1 = \phi_2 = 0$

in the auxiliary model in equation (8). The standard critical values cannot be used to test for the unit root. Accordingly, Sollis (2009) derives asymptotic distribution of an F-test and tabulate critical values for zero mean non-zero mean and deterministic trend cases.

After using aforementioned tests to detect the series which would present a nonlinear behaviour, we conduct ESTAR and AESTAR estimations for these selected countries.

We implement three alternative exercises at this stage. First, as suggested by Kapetanios et al. (2003) and Sollis (2009) we examine the adjustment process towards the *mean*. Then, we further extend this analysis, assuming that the attractor for the series is not the mean but the announced *inflation-target*. This modification in the attractor brings up with two complications: First, the inflation target varies through time for most of the countries. Hence, rather than de-meaning the series for the whole sample, we take into account the deviations from the *shifting target rate* at every point in time in our sample. Second, many inflation-targeting countries announce a *target range* rather than a point target. To take this into account, we carried out two alternative exercises. First, we calculated the target as the *mid-point* of the target range. In this scenario, we assume that the central bank is relatively strict around the mid-point target and assumes the target range as a variation band around this mid-target. In the second case, we measured the target as the *upper limit* of the band. In this scenario, we assume a relatively dovish central bank whose reaction is relatively weaker from deviations from the mid-target compared to the previous case, but gets stronger once inflation jumps above the upper band.

II. Data, Preliminary Diagnostics and Estimation

Our empirical investigation includes unit root tests, structural break tests, linearity tests, ESTAR and AESTAR estimations as well as an out-of sample forecasting exercise over monthly inflation series for nineteen inflation-targeting countries comprising of fourteen emerging markets; Brazil, Chile, Colombia, Czech Republic, Hungary, India, Mexico, Peru, Philippines, Poland, Romania, South Africa, Thailand, Turkey and five developed countries; Canada, Israel, Norway, Sweden and UK[10].

Table 1 presents the countries in our sample and transition year of each country to the IT regime in the first column[11]. Our monthly data set starts at the transition date to IT and ends at March 2013for all countries. The number of observations for each country is presented in the second column. An important prerequisite for nonlinearity tests is a sufficient number of observations at different regimes. However, for some countries in our sample, we have insufficient number of negative deviations to conduct the tests. In such cases where the negative deviations from the target constitute less than twenty percent of the whole IT period (such as Hungary, Mexico, Romania and Turkey as indicated in the third column of the table), a remedy for increasing this number would be using the upper limit of the band as the attractor. However, all of these four countries announce a point target instead of a target band. Nonetheless, these countries announce a *deviation band* which would serve as a threshold above which central bank commits to provide an explanation to the public for the excessive deviation from the target. Consequently, for these four countries, we employed the upper limit of the deviation band as the attractor. The percentage of negative deviations from the attractor goes up above 20 percent for these four countries that are indicated by a star in a new row below the original case in Table 1. For example, for Mexico, negative deviations in whole

[10] Inflation data is taken from Bloomberg whereas the sources for inflation targets are either central bank websites or inflation reports.

[11] While the table denotes a single year for the official adoption of the IT regime, the transition to a full-fledged IT regime was not immediate for most countries. Instead, many countries have gradually developed their implementation capacity over years. A recent IMF study, Ltaifa (2012), documents that this transition phase was around 2 to 5 years for most of the countries that adopted IT regime. During this period, many of these countries conducted an implicit IT regime by either announcing an informal target or a band which operates as an anchor to lower uncertainty and influence expectations. For most of the countries in our sample, these informal targets are also included if these targets are announced by the central bank in an official statement such as monetary policy announcements or inflation reports.

sample increases from 1 percent to 42 percent once we take into account the deviations from the upper limit of the deviation band instead of the target.

Table 1

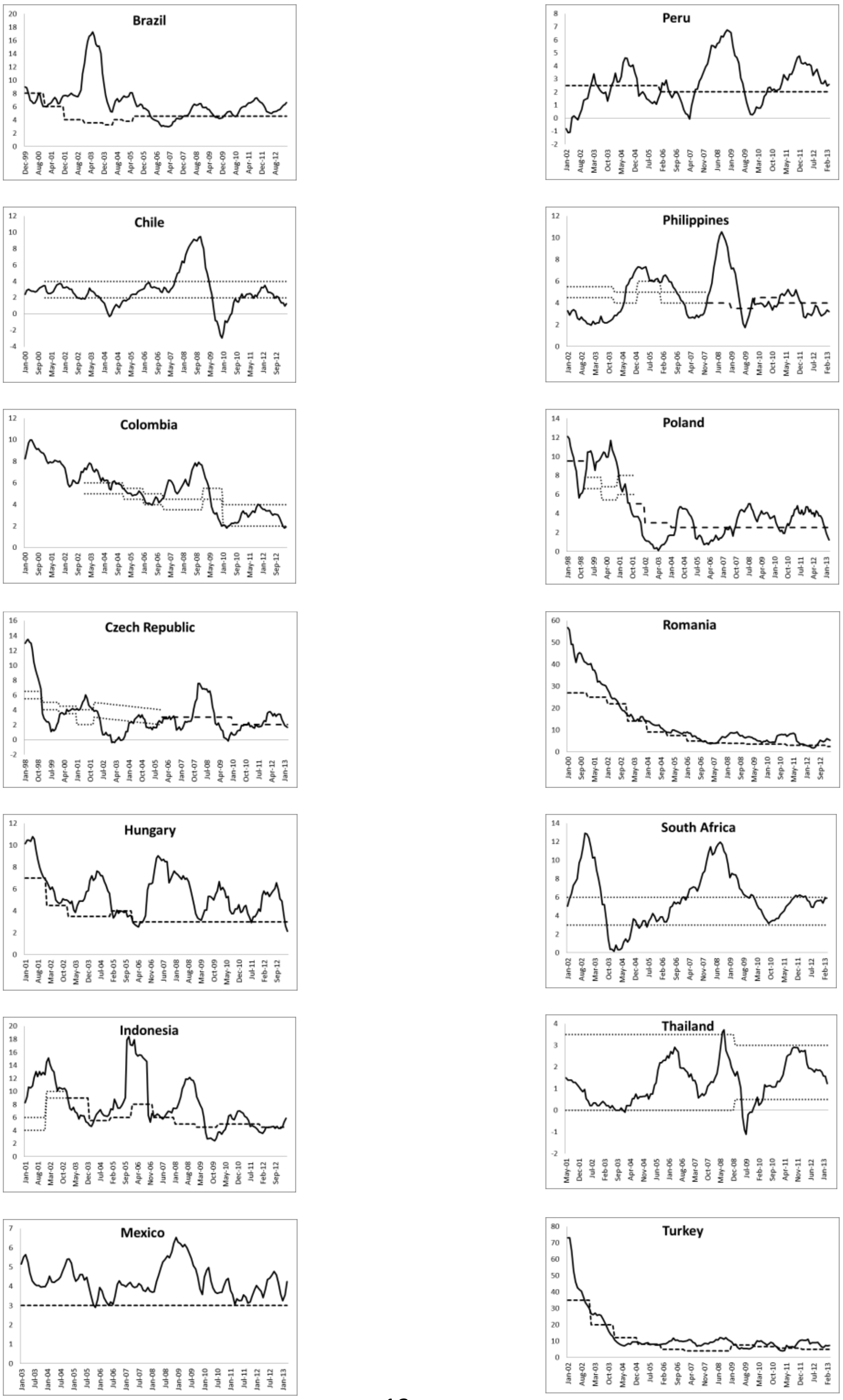
Inflation-Targeting Adoption Date and Sign of the Deviations from the Target

Country	IT Adoption date	# of obs.	% of (-) deviations from target	% of (+) deviations from target
Brazil	1999	170	22	78
Canada	1993	207	51	49
Chile	2000	160	66	34
Colombia	2000	159	33	67
Czech Rep.	1998	183	64	36
Hungary	2001	147	14	86
Hungary*			24	76
Indonesia	2001	147	30	70
Israel	1997	195	51	49
Mexico	2003	123	1	99
Mexico*			42	58
Norway	2001	207	70	30
Peru	2002	135	42	58
Philippines	2002	135	57	43
Poland	1998	183	45	55
Romania	2000	159	13	87
Romania*			26	74
S. Africa	2002	135	33	67
Sweden	1993	207	75	25
Thailand	2001	143	67	33
Turkey	2002	235	17	83
Turkey*			23	77
UK	1992	123	34	66

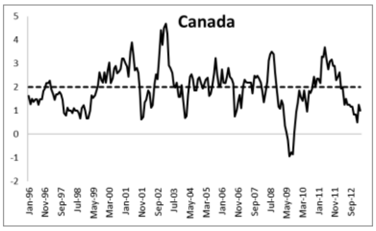
Source: Central Banks' websites, inflation reports and monetary policy announcements.

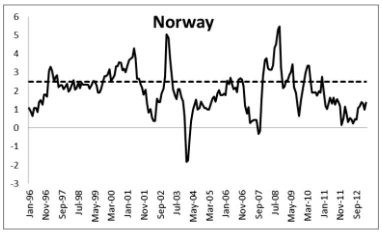
Figure 1: Inflation-Targeting: Target Inflation and Realizations
(Straight lines: actual inflation, thin dashed lines: target band, thick dashed lines: point target)

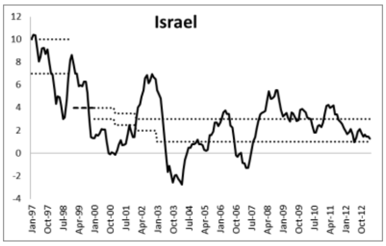
a) Emerging Markets



b) Developed Economies







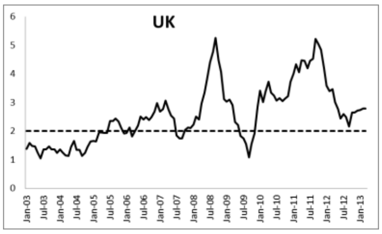


Figure 1 depicts the inflation targets and realizations for all countries through the inflation targeting period. A first look at the graph suggests that many of the emerging markets display a rapid disinflation period at the beginning of the IT period. Accordingly, for many countries inflation targets display a downwards trend. Moreover, for some countries such as Czech Republic, Indonesia, Israel, Philippines or Poland, both a point target and a target band is used along different intervals during IT period. These unstable dynamics suggest possible presence of multiple structural breaks in these series. Accordingly, we conduct and report the results of structural break tests in the next section and further motivate our methodology. The following subsection presents the linear and nonlinear unit root test results. The last subsection provides a discussion of the estimation results before we proceed to the out-of-sample exercise in the next section.

III. a. Structural break test

Rapach and Wohar (2005) reports evidence of multiple structural breaks in the mean inflation rate for 13 industrial countries, using Bai and Perron (2003, hereafter BP) methodology. We conduct a
similar analysis for inflation-targeting countries in our sample. The first two columns of Table 2 are double maximum test statistics with null hypothesis of no structural break against an unknown number of breaks as described in BP. The following five columns, F(i/0) with i=5, tests are for no breaks versus a fixed number of breaks[12,13].

Double maximum test statistics suggest the presence of multiple structural breaks for seven countries out of nineteen. Both UDmax and WDmax statistics are significant for Canada, Colombia, Hungary, Indonesia, Romania and Sweden whereas only the former one is significant for Poland. Moreover, for Philippines, F(5/0) test is also significant at 1 per cent level. Once the presence of breaks is established, BP suggests the use of BIC criteria in order to determine the number of break points. Hence, while other F(i/0) statistics are also significant for some cases, we consider BIC criteria which suggest four breaks for Poland and

[12] Trimming value is selected as 0.15 as suggested by BP.
[13] We also applied F(l+i/i) tests for l breaks versus l+1 breaks as proposed by BP. The results are insignificant, hence not reported but are available upon request.

five breaks for the rest. The last column of Table 2 documents these break dates. For most of the countries, 2008 global crisis and 2010 Eurozone crisis seem to cause a break in inflation[14].

Table 2

Test for Multiple Structural Breaks (Bai-Perron, 2003)

	Udmax	Wdmax	F(1/0)	F(2/0)	F(3/0)	F(4/0)	F(5/0)	Break Dates
Brazil	2.89	5.82	0.57	0.33	0.31	2.89	2.32	
Canada	15.55 ***	18.28 ***	15.55 ***	1.61	1.54	8.65 ***	7.30 ***	Sep-98, Jun-01, Jan-04, Nov-06, Aug-10
Chile	0.82	2.06	0.24	0.61	0.52	0.65	0.82	
Colombia	11.72 **	29.33 **	4.09	4.70	8.87 ***	6.85 ***	11.72 **	Dec-01, Nov-04, Feb-07, May-09, Apr,11
Czech Republic	1.88	2.47	1.37	1.88	1.01	0.75	0.49	
Hungary	12.01 **	19.42 ***	0.11	4.27	12.01 ***	8.78 ***	6.97 ***	Oct-02, Nov-04, Sep-06, Aug-08, Jun-10
Indonesia	13.19 ***	25.47 ***	4.49	13.19 ***	10.12 ***	8.70 ***	10.18 ***	Dec-02, Dec-04, Oct-06, Apr-09, May-11
Israel	6.22	6.22	6.22	1.38	1.22	1.14	0.97	
Mexico	4.45	7.20	1.20	0.44	4.45	3.37	0.79	
Norway	8.36	8.36	8.36	1.04	2.39	1.87	1.67	
Peru	4.59	6.03	0.24	4.59	2.10	1.95	1.55	
Philippines	7.21	53.35	0.63	0.64	1.75	7.21 ***	7.20 ***	Jul-04, Apr-06, Nov-07, Jul-09, Jul-11
Poland	7.99 *	9.94	7.99 *	5.17	5.44 *	5.01 **	2.45	Jul-01, May-05, Oct-07, Jan-10
Romania	35.97 **	51.63 ***	19.23 ***	35.97 ***	25.02 ***	25.29 ***	20.63 ***	Nov-01, Oct-03, Feb-06, Jan-08,Apr-11
South Africa	3.85	8.64	0.29	1.23	1.34	3.85	3.45	
Sweden	15.04 ***	19.75 ***	10.55 **	15.04 ***	10.25 ***	8.51 ***	6.74 ***	Dec-99, Jul-02, May-05, Dec-07, Jul-10
Thailand	5.40	13.51	2.09	0.57	2.33	4.95	5.40	
Turkey	5.57	5.57	5.57	3.94	2.95	2.13	1.70	
UK	7.13	7.13	7.13	3.03	3.70	3.02	2.24	

Notes: *, **and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The impact of structural breaks in our analysis could be observed on two different stages: linearity tests and estimation. Regarding the first issue, Carrasco (2002) shows that tests with a threshold alternative have more power against parameter instability that stems from structural change. However, when the data generating process has a nonlinear character, the power of structural change tests is low. Hence, it is suggested to use threshold type linearity tests to detect the presence of a shift. To put it another way, tests including threshold model, as we will present in the next section, identify parameter instability in time series regardless of its nature.

The second issue is the effect of structural change on estimation and ultimately on the robustness of forecasts. Structural break might induce a bias on forecasts in the sense that

[14] In addition to these common break dates, a change in monetary policy could lead to a shift for individual countries, most probably with some lags.

forecasts are derived from the most recent observations instead of an average one. However, Teräsvirta (2005) argues that while estimation with post-break specifications might lead to an unbiased forecasts, the variance might be greater compared to the model including pre-break data with lower mean square errors. This bias-variance trade-off is further detailed in Pesaran and Timmermann (2002).

As discussed above, Table 2 suggests that latest global crisis in 2008 and Eurozone crisis in 2010 caused a structural shift for many countries in our sample. Hence, using post-break series would sharply reduce our data coverage which would significantly increase the variance. Accordingly, we opt to use whole sample covering IT period for all countries. Obviously, forecasters that would use these models in future should compare the performance of estimations with post-break series, once more data points are available.

III. b. Linear and Non-linear Unit Root tests

The stationarity of inflation is a methodologically essential issue for robustness of the predictive models in use. Indeed, employing linear unit root tests, literature suggests that many price indices have an integration of order one. Furthermore as Gregoriou and Kontonikas (2006) argues, a typical IT implementation suggests that, not only the inflation level but also deviations of inflation from a pre-specified target level could be stationary as discussed in the previous section. As the argument goes, central banks react to deviations from the inflation target which would lead to the inflation to stabilize around the target level in the long-run. This view could be tested by the help of nonlinear unit root tests.

We employ two Augmented Dickey Fuller (ADF) type tests, namely ADF and ERS tests; Phillips-Perron test and Perron (1997) test that accounts for possible structural breaks. Almost all series display an integration of order one character[15]. Since both ESTAR and AESTAR estimations of the next subsection make use of self-exciting threshold variables, this I(1) result ensures the stationarity of threshold variables in those estimations.

[15] Linear unit root test results are not provided due to space limitations but available upon request.

Table 3 presents ESTAR and AESTAR joint tests of unit root and nonlinearity as described in previous section. Eight countries out of nineteen display either ESTAR or AESTAR type nonlinearity. Among the six countries that present ESTAR type nonlinearity, test results are significant at 1 % for Sweden and Thailand, 5% for Israel and UK and 1% for Romania and Turkey. Again six countries out of nineteen display AESTAR type nonlinearity with Romania, Sweden and Turkey at 1%, Thailand at 5% and Canada and Norway at 10%. Accordingly, we exclude eleven countries with insignificant test results from our forecasting exercise with nonlinear models that we present in the next section. The reason behind our exclusion is that, as argued by Teräsvirta (2005), fitting a nonlinear model to a linear time series would generate inconsistent parameter estimates that would lower the robustness of forecasts.

Table 3

Nonlinear Unit Root Tests

	t_{estar}	F_{aestar}		t_{estar}	F_{aestar}
Brazil	-1.82	0.79	Peru	-0.93	1.39
Canada	-2.32	4.24 *	Philippines	-2.21	1.45
Chile	-1.95	1.40	Poland	-2.05	0.76
Colombia	-1.52	1.03	Romania	-2.78 *	17.88 ***
Czech Rep.	-2.34	1.90	S. Africa	-2.62	2.18
Hungary	-2.62	1.46	Sweden	-3.51 ***	9.58 ***
Indonesia	-2.44	2.73	Thailand	-5.43 ***	4.58 **
Israel	-3.28 **	2.71	Turkey	-2.71 *	9.18 ***
Mexico	-1.16	3.25	UK	-3.48 **	3.28
Norway	-1.74	4.62 *			

Notes: *, **and *** indicate significance at the 10%, 5%, and 1% levels, respectively. t_{estar} and F_{aestar} denote t-statistics for ESTAR test and F-statistics for AESTAR test, respectively. The critical values are -3.48, -2.93, -2.66 for ESTAR and 6.806, 4.971, 4.173 for AESTAR, for 1%, 5%, and 10% levels respectively. Lags are chosen by AIC.

III. c. Model Estimation

In order to produce forecasts from the nonlinear models, we estimate ESTAR model for Israel, Romania, Sweden, Thailand, Turkey and UK; AESTAR model for Canada, Norway, Romania, Sweden, Turkey and Thailand. To the best of our knowledge, this paper is the first that would discuss the forecasting performance of AESTAR models. Hence, our focus is on the results of AESTAR estimations in this section. We document the results of the out-of-sample forecasting analysis for both ESTAR and AESTAR models in the next section[16].

After rejecting the linearity hypothesis for eleven countries in the previous section, the AESTAR model is estimated in its raw form in Equation 4 with restrictions $\theta_1, \theta_2 > 0$ and a_1, $a_2 < 0$. Table 4 documents the set of $\{\theta_1, \theta_2, a_1, a_2\}$ values for each country. The figures in parenthesis are standard errors[17,18].

As discussed in the previous section and described in more detail in Sollis (2009), asymmetry requires $a_1 \neq a_2$. Otherwise, the system would be closer to an ESTAR model then an AESTAR one. In the model, the degree of asymmetry and speed of transition are determined by the difference $(a_1\text{-}a_2)$ and the coefficient θ_1, respectively. Furthermore, for a given value of $(a_1\text{-}a_2)$ difference, the magnitude of θ_2 gives an idea of the degree of asymmetry. Accordingly, for Romania and Thailand a relatively higher θ_2 value indicates a relatively more asymmetric behaviour around the attractor, compared to the rest of the group.

The sign of the $(a_1\text{-}a_2)$ difference is also of interest for our analysis. For example, for Sweden, when the inflation is below its attractor, the combined function:

$$G\left(0.04, \pi^*_{t-1}\right)\left[S\left(0.11, \pi^*_{t-1}\right)(-0.13) + \left\{1 - S\left(0.11\pi^*_{t-1}\right)\right\}(-0.11)\right]\pi^*_{t-1}$$

changes between -0.11 and 0. However, when the inflation is above its attractor, the function changes between -0.13 and 0. Consequently, for a country with a negative $(a_1\text{-}a_2)$ difference,

[16] The results of the ESTAR model estimation are not provided due to space limitations but available upon request.

[17] Both ESTAR and AESTAR unit root tests are designed to allow for a time trend in the series. However, in our case, theory would not suggest any trend in inflation series. Hence, we did not use a time-trend in linearity tests or estimations.

[18] For some parameters, the estimation returns the smallest value to comply with the restrictions. For these cases, standard errors are very close to zero.

the mean-reverting behaviour is stronger once the inflation is *above* the mean, relative to the adjustment in case of a negative deviation. As discussed in the introductory section, this could indicate that the impact of the central bank's response offsets the persistence effect . As the argument goes, once the inflation is *above* the mean, central bank takes on a more aggressive policy response towards inflation. Even though there might be a certain degree of inflation persistence, this would be outweighed by the strong policy response of the central bank, hence the adjustment towards the target level is relatively *sharp*. However, once the inflation is *below* the mean, the adjustment towards mean takes more time compared to the previous case.

Table 4

AESTAR Model Estimation

	θ_1	θ_2	a_1	a_2	$a_1 - a_2$
Canada	0.06	0.10	-0.11	-0.11	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	
Norway	0.04	0.08	-0.10	-0.13	0.03
	(0.00)	(0.00)	(0.00)	-(0.04)	
Sweden	0.04	0.11	-0.13	-0.11	-0.02
	(0.01)	(0.02)	-(0.01)	-(0.02)	
Romania	0.10	0.45	-0.03	-0.10	0.07
	(0.00)	(0.20)	(0.00)	(0.00)	
Thailand	0.01	0.19	-0.01	-6.23	6.22
	(0.00)	(0.00)	(0.00)	(0.00)	
Turkey	0.01	0.03	-0.01	-0.35	0.34
	(0.00)	(0.01)	(0.04)	(0.00)	

Notes: Figures in parenthesis are standard errors. *, **and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The opposite is the case for the rest of the countries; Canada, Norway, Romania, Thailand and Turkey. This time the adjustment towards mean is stronger once the inflation is *below* its attractor compared to the adjustment once the inflation is above its attractor. This suggest that once the inflation is *above* the mean, inflation is so persistent that even though there might be a strong response by the central bank, adjustment takes a longer than the similar case in previous paragraph. When the inflation is *below* the mean, the adjustment is sharp due to strong persistence and a relatively weaker policy reaction. It is important to underline that these results do not provide a comparison between the countries in these two groups, in terms of the strength of their policy response or the degree of inflation-persistence. Instead, our results suggest a comparison of *relative* strength of these competing drives above or below the attractor.

Lastly, as indicated in Sollis (2009) a higher coefficient θ_1 indicates a higher speed of transition. Accordingly, a final look at Table 4 highlights that for Romania and Canada the mean-reverting behaviour is relatively faster compared to the rest of the group.

IV. Out-of-Sample Forecasting Analysis

Central banks make use of alternative econometric models as well as expert judgements for forecasting inflation[19]. Throughout these analyses, out-of-sample forecasting exercises are frequently employed in order to compare the predictive power of alternative models. A good in-sample forecasting performance of a model does not necessarily indicate a good performance during an actual forecasting practice. Hence, we conduct an out-of-sample forecasting exercise to assess the forecasting performance of our nonlinear models for eight inflation-targeting countries in our sample.

We divide our sample period into two parts for each country: the training sample which starts from the beginning of the IT date and ends at 2011M09; and the forecasting sample (2011M10: 2013M3). As a first step, we derive forecasts from the estimation using the training sample and derive 1,3,6,9 and 12 months-ahead forecasts. Then, we extend the estimation period one period at a time and report the forecasts at each step again. This exercise is repeated until the end of pseudo out-of-sample period. Then, the result of this rolling out-of-sample exercise is compared with that of a naïve random walk model by means of relative root mean square errors (RRMSE) for each forecast horizon.

[19] Forecasts from these different models and judgements usually complement each other in the course of generating a single-best forecast. Usually, the final forecasts that are reported are produced as a combination of the forecasts from different models including expert judgements. For details of the forecast combination technique see Timmermann (2006).

The results of out-of-sample forecasting exercise for ESTAR and AESTAR models are reported in Table 5 . In the table, columns represent alternative forecast horizons. While the results are mixed for different countries a first look at the table averages suggests that the predictive performance of the model is relatively better in long-horizons rather than short-term.

Table 5

a) RRMSE's of the Out-of-Sample Exercise (ESTAR)

	h=1	**h=3**	**h=6**	**h=9**	**h=12**
Israel	1.36	1.20	0.85	0.67	0.65
Romania	0.76	0.81	0.84	0.82	0.99
Sweden	1.08	0.99	0.90	1.01	0.52
Thailand	1.16	0.91	0.74	0.81	0.85
Turkey	0.76	0.66	0.65	0.33	0.24
UK	1.00	1.10	1.12	1.15	1.17
average	**1.02**	**0.95**	**0.85**	**0.80**	**0.74**

b) RRMSE's of the Out-of-Sample Exercise (AESTAR)

	h=1	**h=3**	**h=6**	**h=9**	**h=12**
Canada	2.65	1.90	1.33	0.97	0.91
Norway	3.99	2.84	2.14	1.38	1.11
Sweden	3.37	2.58	2.43	1.86	1.77
Romania	0.66	0.54	0.48	0.05	0.08
Thailand	1.47	1.24	1.05	1.88	2.30
Turkey	0.78	0.61	0.62	0.23	0.17
average	**2.15**	**1.62**	**1.34**	**1.06**	**1.06**

Note: h denotes the forecast horizon.

The first part of the table documents the RRMSE's of the ESTAR model compared to the random walk benchmark. For Romania and Turkey, the forecasting performance of the ESTAR model is better than that of the random walk in all horizons, although the figures are not so much lower from 1 in Romania. In Turkey, the longer the horizon, the better the forecasting power. The figure is as low as 0.24 in a year ahead forecast horizon. For UK, the performance of the ESTAR model is poor. For the rest of the countries, there are slight improvements in forecasting performance as compared to the random walk, especially in long-run such as 0.52 in Sweden for one year ahead forecasts.

The second part of the table documents the RRMSE's of the AESTAR model compared to the random walk benchmark. Similar to the ESTAR exercise above, the model provides relatively better forecasts for Romania and Turkey. For both countries, the longer the horizon, the better the forecasting power; as low as 0.07 in Romania and 0.16 in Turkey[20]. For the rest of the countries, forecasting power of the AESTAR model is generally poor.

In sum, two result stand out from the forecasting exercise. First, the forecasting power of both models is relatively better only for two countries, Romania and Turkey. Second, predictive performance of the model is especially better in long-horizons. This puzzling result corroborates with some previous studies in the literature. For example, Kilian and Taylor (2003) suggests that the predictive power of ESTAR model for exchange rate determination relative to that of a random walk is higher in longer-horizons. Similarly, Altavilla and De Grauwe (2010) compares the forecasting power of alternative models for exchange rate determination and conclude that the nonlinear models are superior relative to the linear ones in longer-horizons, particularly when the deviations from long-run mean is large. That being said, there is still no consensus on the predictive performance of nonlinear models with respect to the linear ones[21].

As discussed in the second section, we replicated the same analysis with alternative choices of the attractor. In the first scenario, we assumed that the central bank reacts to the deviations from a long-run mean of the series. In the second case, we used the upper limit of

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[20] We also conducted Diebold-Mariano (2002) test which provides a comparison of the forecast accuracy of alternative models. For each country, we strongly reject the null hypothesis of equal forecast accuracy of random walk and AESTAR models. The test is only conducted for the longest series of the forecasting sample (2011M10: 2013M3) due to the finite sample problem. In all tests, p-values are almost zero and are not reported due to space considerations. The results are available upon request.

[21] Two studies that provide mixed evidence on the forecasting accuracy of nonlinear models with respect to linear ones are Terasvirta et.al (2005) and Ferrara (2013) which employs 23 macroeconomic variables of 18 OECD countries.

the inflation target band where a band is available instead of a point target for a specific country. In both cases, the results are generally similar[22].

V. Conclusion

This paper explores the asymmetric behaviour of inflation around a pre-determined target level in inflation targeting countries around two motivations. First one is the supposition that central banks might assign more weight to other objectives if the inflation is under control, yet fight with inflation aggressively if inflation is above the target level, provided that the deviation is above a certain threshold. Second one is asymmetric inflation persistence. It is suggested that the ESTAR model and the recently proposed AESTAR framework helps us to model such asymmetries in the inflation behaviour. Following the steps of nonlinear model building, i.e. linearity testing, model specification, estimation; and further conducting an out-of-sample forecasting exercise we show that the predictive power of ESTAR and AESTAR models could be high for inflation for some countries, especially at longer-horizons. We believe that our results would be beneficial for researchers and in particular central bankers in search of accurate inflation forecasts.

[22] The results are not reported due to space considerations and available upon request

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