# Measuring the Core Inflation in Turkey with the SM-AR Model

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**Abstract**

This paper employs a new econometric technique to estimate the core inflation in Turkey measured as the shifting means in levels between 1955 and 2014. Using monthly series, we determine the number of shifts using the BIC, the $hv$-block cross-validation, the Lin-Terasvirta parameter constancy test, and the neural networks test for neglected nonlinearity. We find that there are at least three shifts in the inflation series. The findings help detect the exact dates of the shifts between different inflation regimes and the duration of each shift, which should be important information in evaluating the success of past economic policies in fighting inflation.

Keywords: inflation; shifting mean autoregressive model; transition function

## 1 Introduction

For the large part of 1980s and throughout the 1990s, Turkey experienced very high and volatile inflation rates[1], which have been subject of many empirical studies. These studies mostly focused on explaining the reasons behind the high inflation. For instance, Metin (1995) notes that the main reason is excessive growth of the money supply, which is caused by fiscal expansion such as to cover the budgetary deficits of public enterprises. Us (2004) attributes the high inflation to the increases in public sector prices and the depreciation of the Turkish lira. She also concludes that inflation has not been a result of an expansionary monetary policy. Dibooglu & Kibritcioglu (2004) employs a vector autoregressive framework and finds that terms of trade shocks affects inflation in the short-run whereas monetary and balance of payments shocks dominate in the long-run. They also point out to inflationary expectations. Other studies focused on the relation between inflation levels and inflation uncertainty measured by volatility. For instance, Nas & Perry (2000) finds strong statistical evidence that inflation affects inflation uncertainty but their evidence on the opposite relation is not clear-cut. Similarly, Ozdemir & Fisunoglu (2008) finds

[1] See Metin (1995), Kibritcioglu et al. (2002), and Nas (2008).

that there is empirical support that higher inflation causes more inflation uncertainty but not the vica versa. Berument et al. (2011) also finds positive and significant relation between inflation and inflation volatility.

Even though there is no shortage of empirical studies providing explanations behind the high inflation in Turkey, research on the core inflation is suprisingly scant. Among the few ones are Berkmen (2002), which employs a trimmed mean approach and Atuk & Ozmen (2009), which employs the same approach taking into account the seasonal adjustment. This paper uses a new econometric method, namely the shifting-mean autoregressive model (SM-AR), developed by Gonzalez & Teräsvirta (2008) to estimate the core inflation in Turkey. In this method, the core inflation is measured as a series of shifts in the mean level. However, the method is perfectly capable of taking into account the autoregressive structure in the inflation levels.

The paper is organized as follows. Section 2 presents the SM-AR model and several methods to determine the number of shifts in the inflation mean. Section 3 discusses the data. Section 4 presents the results. Section 5 concludes the paper.

## 2 The SM-AR Model

The stationary autoregressive model with a shifting mean of order $p$, SM-AR$(p,q)$, is proposed by Gonzalez & Teräsvirta (2008) and applied to inflation forecasting by Gonzalez et al. (2011). The model is represented as follows

$$y_t = \delta\left(t\right) + \sum_{j=1}^{p} \phi_j y_{t-j} + \varepsilon_t \tag{1}$$

where $y_t$ is the series, $\varepsilon_t \sim IID\left(0, \sigma^2\right)$ and $\delta\left(t\right)$ is a deterministic nonlinear shift function, which is defined as

$$\delta\left(t\right) = \delta_0 + \sum_{i=1}^{q} \delta_i g\left(\gamma_i, c_i, t/T\right) \tag{2}$$

The function $g\left(\cdot\right)$ is the logistic transition function

$$g\left(\gamma_i, c_i, t/T\right) = \left(1 + \exp\left(-\gamma_i\left(t/T - c_i\right)\right)\right)^{-1} \tag{3}$$

where it is assumed that $0 \leq c_1 < \cdots < c_q \leq 1$. The equations 1, 2, and 3 together constitute the SM-AR model. The parameters to be estimated are $\phi_j$, $\delta_0$, $\delta_i$, $\gamma_i > 0$, and $c_i$ where $j = 1, \ldots, p$ and $i = 1, \ldots, q$. $\gamma_i$ is called the smoothness parameter and $c_i$ is the location parameter. Together with $\delta_i$, $\gamma_i$ and $c_i$ control the movement of the shifting mean. $\gamma_i$ controls the sharpness of the shift. If it is large, the shift is abrupt. On the other hand, if it is small, the shift is smooth. $c_i$ controls the location of the shift. Since $t/T$ is between 0 and 1, $c_i$ is also in the same range. $\delta_i$ controls the direction of the change in the shifting mean. Put differently, each $\delta_i$ represents a break and the model contains

$q+1$ regimes. If it is negative (positive), the mean decreases (increases). $q > 1$ adds flexibility to the model in such a way that several shifts can be modeled.

Notice that the SM-AR model is a nonlinear deterministic trend stationary model. It is similar to the "single hidden-layer" artificial neural network (ANN) model. Gonzalez & Teräsvirta (2008) proposed an algorithm called `QuickShift`, which not only estimates the model parameters but also estimates $p$ and $q$ as part of the estimation process. `QuickShift` consists of the following steps

1. Estimate the model in equation 1 assuming $\delta(t) = \delta_0$ with the ordinary least squares (OLS) and obtain the residuals $\hat{\varepsilon}_{t,0}$ and the Bayesian Information Criterion (BIC).

2. Create a grid for $\gamma_i$ and $c_i$. Notice that the model is a linear one when $\gamma_i$ and $c_i$ are known. Estimate the model for $q = 1$ using each $(\gamma_i, c_i)$ pair. Select the pair for which the square of the sample correlation

$$Corr\left(g\left(\gamma_s, c_s, t/T\right), \hat{\varepsilon}_{t,0}\right)^2$$

   is maximum. Once again, save the residuals $\hat{\varepsilon}_{t,1}$ and the BIC.

3. Continue in this fashion increasing $q$ by one at each step, selecting the $(\gamma_i, c_i)$ pair for which the square of the sample correlation between the values of the transition function and the residuals from the previous step is maximum, and saving the residuals and the BIC.

4. Stop when $q$ exceeds a pre-determined maximum value, say 5, and select the model for which the BIC is minimum.

BIC is only one of the measures used to select the number of transitions $q$. Gonzalez & Teräsvirta (2008) also use the $hv$-block cross-validation, the parameter constancy test, and the neural network test for neglected nonlinearity. We discuss them next.

$\delta$ shows the degree of change in the mean inflation. $\gamma$ shows how fast the shift happens.

## 2.1 The $hv$-block Cross-Validation

The $hv$-block cross-validation is proposed as a consistent procedure for model selection for stationary dependent data by Racine (2000). In this procedure, the data is split into two distinct sets: training set and validation set. The training set is used to estimate the model whereas the validation set is used to validate it. The procedure is implemented as follows. Let $\mathbf{Z} = (\mathbf{y}, \mathbf{X})$ represent the $N \times (K+1)$ matrix of observations where $\mathbf{y}$ is the $N \times 1$ vector of observations on the response variable and $\mathbf{X}$ is the $N \times K$ matrix of observations on the explanatory variables. We remove observation $i$ from $\mathbf{Z}$ along with first $v$ and then $h$ observations on either side of $i$ and obtain the $(N - 2h - 2v - 1) \times (K+1)$ matrix $\mathbf{Z}_{(-i:h,v)}$, which will be used for estimating the model. The $(2h + 2v + 1) \times (K+1)$ matrix of removed observations and its

$(2v+1) \times (K+1)$ submatrix will be denoted by $\mathbf{Z}_{(i:h,v)}$ and $\mathbf{Z}_{(i:v)}$, respectively. $\mathbf{Z}_{(i:v)}$ will be used in the validation step. In other words, the model is estimated using $\mathbf{Z}_{(-i:h,v)}$ and validated using $\mathbf{Z}_{(i:v)}$. The cross-validation function is given by

$$CV_{hv} \quad = \quad \frac{1}{(N-2v)(2v+1)} \sum_{i=v}^{N-v} \parallel \mathbf{y}_{(i:v)} - \hat{\mathbf{y}}_{(i:v)(-i:h,v)} \parallel^2$$

where $\parallel \mathbf{a} \parallel = \sqrt{\mathbf{a}'\mathbf{a}}$ and $\hat{\mathbf{y}}_{(i:v)(-i:h,v)}$ is the predicted response variable. Models are compared with respect to their $CV_{hv}$ scores and the model with the smallest score is selected.

## 2.2 The Parameter Constancy Test

Following Gonzalez & Teräsvirta (2008), we also apply the parameter constancy test proposed by Lin & Teräsvirta (1994) to determine the number of transition functions. The test is basically a test for the time-varying intercept term $\delta(t)$. Consider the following model

$$y_t = \delta_0 + \delta_1 g(\gamma_1, c_1, t/T) + \boldsymbol{\theta}'\mathbf{w}_t + \varepsilon_t$$

where $\mathbf{w}_t = (y_{t-1}, \ldots, y_{t-p})'$. The null hypothesis of the test is $\gamma_1 = 0$, which can also be expressed as $\delta(t) = \delta_0$. Under the null hypothesis, $c_1$ is unidentified. This is the well-known nuisance parameter problem. Lin & Teräsvirta (1994) solves the problem by replacing $g(\gamma_1, c_1, t/T)$ with its Taylor series expansion around $\gamma_1 = 0$. The auxiliary regression is

$$y_t = \delta_0^* + \sum_{i=1}^{m} \phi_i \left(\frac{t}{T}\right)^i + \boldsymbol{\theta}'\mathbf{w}_t + \varepsilon_t^*$$

The null hypothesis becomes $\phi_i = 0$ for $i = 1, \ldots, m$. Under the null hypothesis, the LM test has an asymptotic $\chi^2$distribution with $m$ degrees of freedom. The F version of the test has $m$ and $T - p - m - 1$ degrees of freedom. Lin & Teräsvirta (1994) recommends $m = 3$ but Gonzalez & Teräsvirta (2008) states that $m > 3$ can be considered in the present context. We use both $m = 3$ and $m = 6$. Since it is possible that the order of the autoregressive lag is misspecified in the search for $q$, Gonzalez & Teräsvirta (2008) advices to use the heteroskedasticity and autocorrelation consistent (HAC) covariance matrix to compute the test statistic. We use the Bartlett kernel with automatic Andrews bandwidth selection. The test can be used to determine $q$ sequentially. Assume it has been decided that $q = 1$ and we want to test for $q = 2$. Then the extended model is

$$y_t = \delta_0 + \delta_1 g(\gamma_1, c_1, t/T) + \delta_2 g(\gamma_2, c_2, t/T) + \boldsymbol{\theta}'\mathbf{w}_t + \varepsilon_t$$

In that case, the null hypothesis is $H_0 : \gamma_2 = 0$. The auxiliary regression is extended as follows

$$y_t = \delta_0^* + \delta_1 g(\gamma_1, c_1, t/T) + \sum_{i=1}^{m} \phi_{2,i} \left(\frac{t}{T}\right)^i + \boldsymbol{\theta}'\mathbf{w}_t + \varepsilon_t^*$$

The null hypothesis becomes $\phi_{2,i} = 0$ for $i = 1, \ldots, m$ and the test can be conducted as explained above. Continuing in this fashion, one can decide the number of transition functions suggested by the data.

### 2.3 The Neural Network Test

The neural network test for neglected nonlinearity is a portmanteau test proposed by Lee et al. (1993). The exposition here follows Franses & van Dijk (2000). Consider the following artificial neural network ANN$(p, q)$ model

$$y_t = \mathbf{x}_t'\boldsymbol{\phi} + \sum_{j=1}^{q} \beta_j G\left(\mathbf{x}_t'\boldsymbol{\gamma}_j\right) + \varepsilon_t \tag{4}$$

In this model, $p$ and $q$ represent the number of lags and hidden units, respectively. $\mathbf{x}'_t = (1, y_{t-1}, \ldots, y_{t-p})$, $\mathbf{x}_t'\boldsymbol{\phi}$ is the linear component, $\sum_{j=1}^{q} \beta_j G\left(\mathbf{x}_t'\boldsymbol{\gamma}_j\right)$ is the nonlinear component, which is also called the hidden layer, and

$$G\left(\mathbf{x}_t'\boldsymbol{\gamma}_j\right) = \left(1 + \exp\left(-\mathbf{x}_t'\boldsymbol{\gamma}_j\right)\right)^{-1}$$

is the logistic function. If $y_t$ is a linear process, then the nonlinear component should be zero or at least a constant. The neural network test is a test for the constancy of this nonlinear component. The nul hypothesis is $H_0 : \beta_1 = \cdots = \beta_q = 0$. The test is implemented in the following steps:

1. Estimate the linear component in equation 4 and obtain the residuals $\hat{u}_t$.

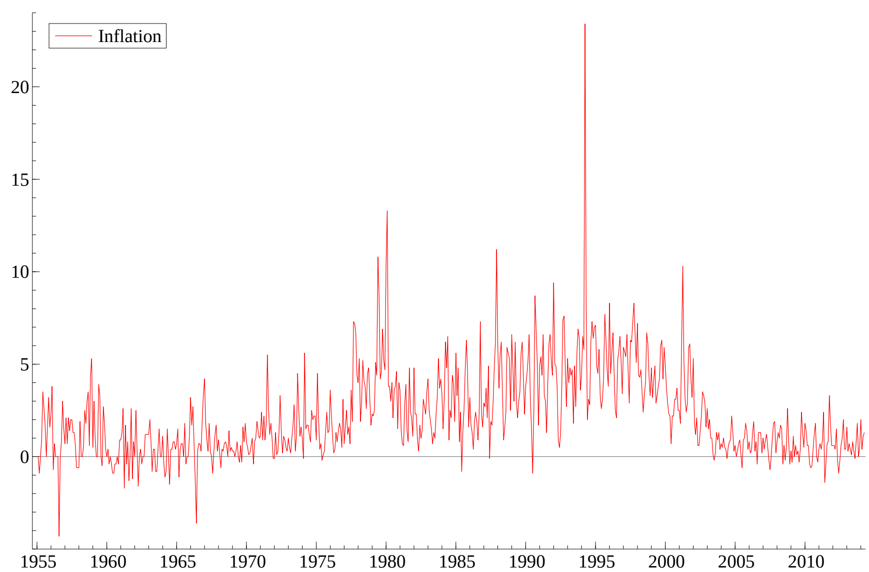
2. Generate $\gamma_{i,j}^*$ randomly from a uniform distribution with support $[-2, 2]$ for $i = 0, 1, \ldots, p$ and $j = 1, \ldots, q$, compute the activation functions $G\left(\mathbf{x}_t'\boldsymbol{\gamma}_j^*\right)$, and use them as regressors in the auxiliary regression

$$\hat{u}_t = \mathbf{x}_t'\boldsymbol{\alpha} + \delta_1 G\left(\mathbf{x}_t'\boldsymbol{\gamma}_1^*\right) + \cdots + \delta_q G\left(\mathbf{x}_t'\boldsymbol{\gamma}_q^*\right) + \eta_t$$

3. Test for $\delta_1 = \cdots = \delta_q = 0$. The test statistic $nR^2$ is asymptotically distributed $\chi^2(q)$ where $n$ is the number of observations used in the estimation.

In order to implement the test, the number of hidden units $q$ must be determined. Lee et al. (1993) suggest a high value such as 10 or 20 in order to capture the potential nonlinearity. However, the generated regressors are likely to be highly correlated when $q$ is set that high. Their remedy for this issue is to use the first 2 or 3 princial components of the generated regressors in the auxiliary regression instead. They also suggest skipping the first component to ensure the orthogonality of the components to the inputs $\mathbf{x}_t$. Another issue with the test is its random nature. The test might be rejected for one set of $\gamma_{i,j}^*$ whereas it might not be rejected for another set. In order to solve this issue, the authors suggest $R$ different draws. The null hypothesis is then rejected at the $\alpha^*$ level if there exists an $r$ value for which $p(r) \leq \alpha^* / (R - r + 1)$ where $r = 1, \ldots, R$.

Figure 1: Turkish Inflation, 1955-2014




# 3 Data

The inflation series in this study comes from the OECD Main Economic Indicators. The series is monthly, covering the period between February 1955 and April 2014, and represents percentage changes from previous period. Figure 1 shows the series. As can be seen from the figure, 1960s were a relatively low inflation period. The main reason for that could be the favorable economic environment created by the large-scale labor migration to West Germany. Unlike 1960s, 1970s were turbulent years. As well known, this period saw two oil crises, which affected the Turkish economy deeply and drove up the price levels considerably. In late 1970s and early 1980s, Turkey experienced severe economic and political crises. This period ended abruptly in 1980 when the Turkish armed forces conducted a coup d'état. Turkey returned to democracy in 1984. However, ill-advised economic policies of the new and the subsequent governments caused high inflation[2], which lasted through late 1980s and throughout 1990s. The worst monthly inflation recorded in the history of Turkey was 23.4 in April 1994, which can be seen as the single spike in the figure. The financial crisis of 2001 created another high-inflation phase in the economy[3]. Turkey has experienced relatively low inflation since 2002 even though its inflation rate is still one of the highest among the OECD countries.

[2]See Chapter 5, Turkish Inflation, in Nas (2008).

[3]See Akyuz & Boratav (2003), Onis & Rubin (2003), and Chapter 6 in Nas (2008).

Table 1: Number of transitions using `QuickShift`

| AR Order | BIC | CV | LT3 | LT6 | LWG |
|---|---|---|---|---|---|
| $p = 0$ | 3 | 4 | 3 | 3 | 3 |
| $p = 1$ | 3 | 5 | 3 | 3 | 3 |

Table 2: SM-AR Models with 3, 4, and 5 transition functions

| AR Order | $p = 0$ | $p = 0$ | $p = 1$ | $p = 1$ |
|---|---|---|---|---|
| $\delta_0$ | 0.7776<br>(6.7477) | 1.2007<br>(4.2572) | 0.4914<br>(4.4536) | 0.8429<br>(3.116) |
| $y_{t-1}$ | | | 0.3762<br>(10.7841) | 0.3711<br>(10.602) |
| $\delta_1$ | 2.5025<br>(13.1454) | $-0.5375$<br>($-1.6433$) | 1.5658<br>(7.948) | $-0.6619$<br>($-1.6875$) |
| $\delta_2$ | 1.7168<br>(7.7525) | 2.626<br>(12.8446) | 1.0543<br>(4.9204) | 0.3678<br>(1.2091) |
| $\delta_3$ | $-4.3668$<br>($-19.3115$) | 1.7071<br>(7.7151) | $-2.724$<br>($-10.5009$) | 1.5212<br>(6.3847) |
| $\delta_4$ | | $-4.3661$<br>($-19.3312$) | | 1.0678<br>(4.9773) |
| $\delta_5$ | | | | $-2.747$<br>($-10.5817$) |

Note: $\delta$ values are ordered with respect to time for each model.

## 4 Results

In this section, we present the results[4]. The inflation series seems to contain several breaks though it is hard to pinpoint their exact dates by visual inspection. In order to figure out the exact dates of the breaks and their duration, we estimate the SM-AR model setting the maximum number of transitions to five. We use the Bayesian information criteria (BIC), the $hv$-block cross validation (CV), the Lin-Terasvirta parameter constancy test (LT), and the Lee-White-Granger (LWG) neural network test for neglected nonlinearity to determine the number of transitions. The setup of `QuickShift` is as follows. For the grid, we set $\gamma \in [0.5, 20]$ and $c \in [0, 1]$ and use 30 different values for each grid, making 900 overall grid pairs. The smoothness parameter is divided by the sample standard deviation of $t/T$ to make it scale-independent. We search for the number of transitions for $p = 0$ and $p = 1$. When computing the test statistics, we use the Andrews HAC estimator for the covariance matrix. The results are shown in Table 1.

As can be seen from the table, `QuickShift` selects mostly three shifts in the mean. LT3 and LT6 represent the Lin-Terasvirta tests with the third and sixth power of the scaled time trend used in the auxiliary regression. The results

[4]All the results in this paper are obtained using the code written by the author in the Ox object-oriented programming language, Doornik (2001).

do not change much if one takes into account the autoregressive order. We experimented with two lags but the coefficient of the second lag turned out to be insignificant. Based on these results, we conclude that the core inflation can be modelled as an SM-AR(1,3) process. In other words, its autoregressive order is one and it contains three breaks (four regimes) in the mean. However, we still estimate the SM-AR models with three, four, and five shifts in order to compare the results, which are shown in Table 2. The values inside the parentheses are the Andrews HAC t-ratios.

The preferred model is the one in column three. We are going to comment on this model only. Interpretation of the results for the other models are similar. The coefficient of the first shift is 1.5658. Its sign shows that this is an increase in the mean value. The location parameter corresponding to this shift is 0.3458[5], which indicates that the shift happened around the 35th percent of the sample. The coefficient of the second shift is 1.0543, which is also positive. This shift took place around the 59th percent of the sample. The final shift is a decrease in the core inflation. The coefficient is $-2.724$ and the location parameter is 0.7934. Notice that the autoregressive coefficient does not change much when the number of transitions is increased from three to five. The fitted inflation series can be seen in Figure 2. The figure on the top is the fit of the model with three transition functions and no lags. The shifts in the mean inflation can be easily seen. The bottom figure shows the fit of the model with three transitions and one lag. The shifts in the mean lag are less obvious because of the zig-zags created by the autoregressive part.

The SM-AR model also helps us detect the exact dates and the duration of the shifts, which are shown for the preferred model along with the parameters of the three transition functions in Table 3. Before the first shift, the monthly core inflation was around a little bit less than 1%. The first shift was an increase in the mean inflation, which started around October 1972 and ended in June 1978 with the center date June 1975. Notice that these dates coincide with the two OPEC oil crises. At the end of this shift, the monthly core inflation stabled between 3 and 4 percent. The second shift was a further increase in the mean inflation, which started around May 1987 and ended in May 1992 with the center date September 1989. At the end of this period, the monthly core inflation was about 5 percent. The main culprits for this second shift were fiscal expansion and non-sterilized purchases of foreign reserves by the Central Bank[6]. The third and the last shift was an unprecedented decrease in the core inflation. It started in August 1999 and ended in August 2004 with the center date December 2001. At the end of this last shift, the core inflation stabled around 1 percent once again. Notice that the SM-AR model does not pick the short-lived hike around 2001.

[5] See Table 3.

[6] Nas (2008), page 73.

Figure 2: Inflation and its SM-AR(0,3) and SM-AR(1,3) Fits

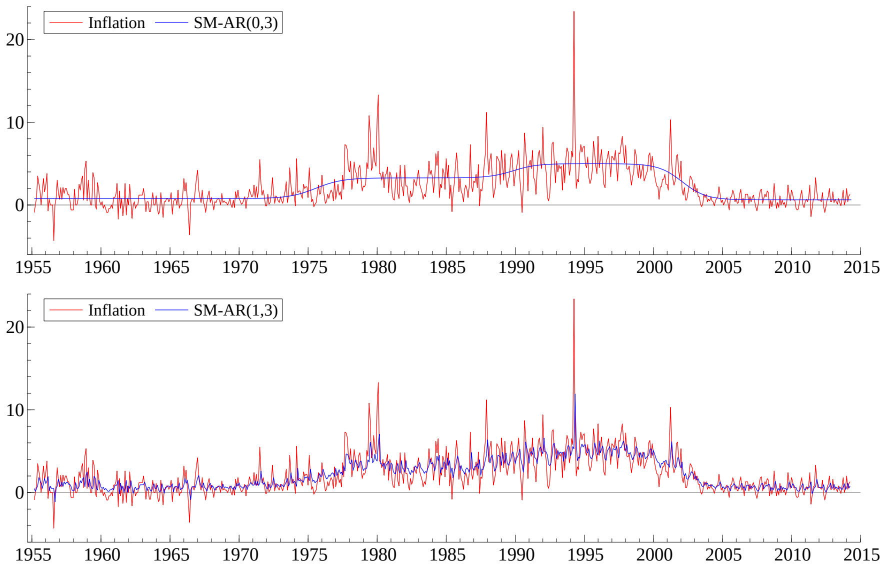



Table 3: Transitions and break dates

| $q$ | $\gamma$ | $c$ | Start | Center | End |
|---|---|---|---|---|---|
| 1 | 17.6111 | 0.3458 | 1972(10) | 1975(6) | 1978(6) |
| 2 | 20 | 0.5868 | 1987(5) | 1989(9) | 1992(5) |
| 3 | 20 | 0.7934 | 1999(8) | 2001(12) | 2004(8) |

## 5 Conclusion

In this study, we used the SM-AR model to estimate the core inflation in Turkey measured as shifting means in the inflation level. The SM-AR model is suitable for describing characteristic features of the core inflation. The findings suggest that there are at least three shifts in the mean inflation, two increases and one decrease. The SM-AR model also allowed us to detect the exact dates and the duration of the shifts. We believe this information should be useful in evaluating the success of the past economic policies in fighting inflation in Turkey.

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