

# INFLATION MODELING

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INFLATION MODELING  
ENFLASYON MODELLEMESİ

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- 1) Enflasyon Modellemesi
- 2) Enflasyon Tahmini
- 3) Zaman Serileri Analizi
- 4) Makroekonometri
- 5) Maliszweksi'nin Denklemi

Anahtar Kelimeler (İngilizce)

- 1) Inflation Modeling
- 2) Inflation Forecasting
- 3) Time Series Analysis
- 4) Macroeconometrics
- 5) Maliszweksi's equation

## Özet

Para, enflasyon, üretim ve kur değişkeni serileri I(1) ve koentegredir. Bu sonuca göre, fiyat seviyesi kur, para ve üretim değerlerinin değişimiyle uzun vadede pozitif ilişki içersindedir. Aynı zamanda, Maliszweksi'nin denklemine göre Türkiye'de enflasyona kısa vadede eşzamanlı kur, para ve üretimdeki değişimin pozitif etkisi vardır. Ek olarak, geçmiş zamanda gelen etkiler Türk ekonomisindeki düzeltici etmenlerin varlığını gösterir. Yine ek olarak, kurdaki değişimin enflasyona etkisinin parasal değişimin etkisine göre daha fazla olması, Türkiye ekonomisinin uluslararası etkenlere ne kadar açık olduğunu gösterir. Bunların yanında, bir önceki çeyreklik dönemdeki enflasyonun şimdiki zamana olan etkisinin Türkiye'de enflasyon beklentilerinin etkisini gösterir. Bu sonuç AR(2) ve TAR modelleri tarafından da doğrulanmıştır. Aynı zamanda, iki rejimli TAR modeli Türkiye enflasyonun iki tane AR(2) prosesi tarafından modellenilebileceğini ve de enflasyonun averaj değerinin üstünde kaldığı süre içersinde daha yüksek olma eğiliminde bulunduğunu gösterir. Özyineleme testleri Maliszweksi'nin denkleminin parametrelerinin ekonomideki yapısal kırılmalardan dolayı belli dönemlerde küçük dengesizlikler gösterse bile, genel anlamda dengeli değerlere sahip olduğunu, olduğunu göstermiştir. Bu durum, Maliszweksi'nin denkleminin tahminlerinin AR(2) ve TAR modellerinin tahminlerine göre daha iyi sonuçlar vermesinden de anlaşılabilir. Kısacası, Türkiye enflasyonun tahmin performanslarının sonuçlarına bakınca, ekonominin yapısını varsayarak kurulan bir model ateoretik modellere göre daha iyi performans göstermiştir.

## Abstract

The money, inflation, output and exchange rate series are found to be I(1) and are cointegrated. Thus, in the long run the price level is positively related to the growth in exchange rate, money and output. On the other hand, in the short run according to the Maliszweksi's equation, Turkish inflation is positively affected by the contemporaneous depreciation and monetary and output growths ( $\Delta \ln(E_t)$ ,  $\Delta \ln(M_t)$ , and  $\Delta \ln(Y_t)$ ). Furthermore, the presence of the lags show the significance of adjustment lags in Turkish economy. Also, the impact of the depreciation is higher than the impact of monetary growth suggesting the exposure of Turkish economy to international effects. In addition, the presence of inflation lag confirms the inflation inertia in Turkey. The finding of inflation inertia by the Maliszweksi's equation is also confirmed by AR(2) and TAR model since the lagged values of inflation were significant. Furthermore, the two-regime TAR model suggests that Turkish inflation can be

modeled with two AR(2) processes and that inflation tend to stay higher when it is above the average inflation rate. In terms of stability tests the parameters of the Maliszweksi's equation were the most stable one though they may have instabilities during certain periods due to the structural breaks in the time series path of Turkish Economy. This is also well confirmed by the fact that Maliszweksi's equation perform better than both AR(2) and TAR models. In sum, a forecast performance taking into consideration the structure of the economy performed better than the two atheoretical models for Turkish case.



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## **1- Introduction:**

Throughout the years a myriad of inflation models are developed by academicians, monetary authorities and firms to forecast inflation. The main goal was to obtain a clear forward looking agenda to define the policies that help the economics agents avoid potential risks hidden in the economy. Especially, with the dominance of inflation targeting approaches in both industrialized and developing countries, inflation forecasts gains further importance for monetary authorities to delegate their policies.

However, forecasting inflation is not an easy task to perform as it involves various approaches that are modeled with an enormous rage of variables. Moreover, the appropriate choice of variables along with a relevant model is another hassle as it depends on the nature of an economy under consideration. Therefore, while forecasting inflation, the structure of a relevant economy should be understood in order to define the approach that will be taken to model the inflation with related variables and techniques.

This thesis proceeds to section 2 with providing a general framework for the inflation studies. This means, it presents the common approach taken for modeling inflation and the variables and models used for analyzing and forecasting inflation. Section 3 conducts a large literature review on the inflation modeling and forecast studies conducted to this date. In section 4, the thesis provides a literature review on the inflation studies conducted to find the causes of inflation in emerging markets and Turkey. Section 3 and section 4 are essential because their aggregation leads to further section where I present a forecast study for Turkish inflation. Thus, section 5 gives the background on the models used for forecasting Turkish inflation and their results. Section 6 summarizes the general conclusion of the thesis.

The main contribution of this thesis is to evaluate a structural model as Maliszweksi (2003)'s equation by comparing it to two atheoretical time series models through the use of Turkish data. One of the time series models is benchmark AR(p) model, and the other one is STAR model. The aim is to provide a clear evaluation of a structural model in regards to a simple atheoretical benchmark model and a model that captures the structural breaks in an emerging market economy.

## **2- General Framework:**

### *2.1- Common Approach*

Inflation is defined as the persistency of the increase in price levels. Inflation forecasting is the study to forecast inflation conditioned on past data. The number of models utilized for forecasting inflation is very large due to the large number of variables present within an economy. The method to forecast inflation depends on the econometricians' selection of the variables given the structure of an economy. Generally, econometricians use three models to forecast inflation. These are benchmark (atheoretical) time series models (linear or non-linear), structural models based on alternative Philips Curve definitions at large extent, and survey results of economics agents' expectations.

Each methodology has its own advantages and disadvantages. The selection criterion for the models is mainly based on in sample measures and pseudo out-of-sample measures. These measures provide an econometrician how well a particular model captures the structure of an economy.

### *2.2- Definition of Variables*

In inflation forecasting, the change in price level is generally computed from the Consumer Price Index (CPI). Thus, the change in CPI is taken as the dependent variable, hence the measure for inflation. However, in some instances core inflation is considered for measuring inflation since CPI may not always be the ideal target for monetary control, and policymakers may prefer to focus on the underlying trend in inflation<sup>1</sup>. In this thesis, the change in CPI is taken as the dependent variable as it was the mainly utilized dependent variable for measuring inflation in the referred articles.

The variables utilized to forecast inflation are grouped under non-financial, financial and survey indicators depending on the nature of the approach taken for the model. Non-financial indicators may be named as macro variables. "They are represented by a long list of indicators as consumption, investment, (un)employment figures, monetary aggregates, fiscal policy indicators etc..."<sup>2</sup>

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<sup>1</sup> Jorge Ivan Canales-Kriljenko, Turgut Kışınbay, Rodolfo Maino, and Eric Parrado (2006), "Setting the Operational Framework for Producing Inflation Forecasts," *Central Bank of Chile Working Papers*, No 362.

<sup>2</sup> Jorge Ivan Canales-Kriljenko, Turgut Kışınbay, Rodolfo Maino, and Eric Parrado (2006), "Setting the Operational Framework for Producing Inflation Forecasts," *Central Bank of Chile Working Papers*, No 362.

Other than non-financial indicators, researchers also utilized financial indicators to forecast inflation. Financial indicators mainly include interest rates, term spreads, term structure, default spreads, financial asset prices, exchange rates, commodity prices, housing prices etc...

Indicators of surveys mainly consist of inflation expectations of the sample population. The population usually consists of professional forecasters, households and firms. In addition, consumer confidence indices may also be a useful indicator in assessing the expected inflation rate in a given economy.

The use of each indicator depends on the nature of an economy under consideration. Thus, a proper way to utilize the variables lay in the approach taken to model the inflation. However, before extending into the approaches taken, the thesis initially represents the models and methods used for inflation forecasting by econometricians. The aim is to provide the background on econometrics models and to show how these models are utilized for inflation forecasting.

### *2.3- Description of Models & Model Selection Methods:*

#### *2.3.1- Description of Models<sup>3</sup>*

Theoretical economic models have traditionally been developed as non-stochastic mathematical entities and applied empirical data by adding a stochastic error to the mathematical model<sup>4</sup>. The methodology in these models was to build a causal relation between inflation and economic indicators as given in the theory. Once the model is defined, a regression analysis is conducted to analyze the impact of indicators to the change in price level. The drawback was that most of these models did not include the time dependent behavior of macroeconomic data. As a result of the lack of consideration of this behavior spurious relations among variables could cause misleading conclusions.

Since the relation between inflation and economic indicators were devised in various reduced form theoretical (or structural) models, then a question of estimation was raised. After Granger and Newbold (1974) showed the spurious relationship of two unrelated variables following a random walk pattern, time series analysis started to take further ground in

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<sup>3</sup> The mathematical interpretation of models may be found at the end of this section.

<sup>4</sup> Katrina Juselius (2002), "Model and relations in economics and econometrics," *Macroeconomics and the real world: Econometric Techniques and Macroeconomics*, Volume 1.

empirical analysis. Especially, in the past twenty years or so applied macroeconomics has been transformed by the widespread adoption of a set of time series techniques<sup>5</sup> where empirical data was modeled as time dependent stochastic processes<sup>6</sup>.

Within the time series analysis framework, the main goal was to remove the stochastic trend in the variables through differencing. A stochastic trend makes economic series non-stationary. The method provided by Box and Jenkins (1970) showed that the trend in series could be removed through differencing. Thus, if the trend in a non-stationary variable is removed through first differencing, then that variable is called I(1) stationary, where “I” stands for integration and the number in the parenthesis gives the order of integration. In order to test whether the variable under consideration is stationary, Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979) or a series of other tests may be utilized to test the unit root hypothesis. In this test, the aim is to find out whether the coefficient of the autoregressive terms is equal to 1. Through ADF test, we may deduce that series are non-stationary if the coefficient of the autoregressive terms is equal to 1. In general, most economic series are I(1), indicating that they mostly contain stochastic trend. Therefore, most economic series may be transformed to stationary series through first differencing.

Box-Jenkins approach allowed the autoregressive distributive lag (ARDL) models (models of the London School of Economics (LSE) tradition) to be written in the error-correction form. This form, in turn, led the evolution of error correction models (ECMs). These models worked well in many economic applications, by being both able to fit the data and to be interpreted in terms of long-run economic theory<sup>7</sup>. Moreover, variables of models built under ECM approach were also said to cointegrate (Engle and Granger, 1987).

Cointegration is basically a technique to test the correlation between non-stationary series. If the regression of an I(1) variable to another variable (or other variables) is not spurious, then they are said to cointegrate: the linear combination of the variables are stationary. Thus, with the advent of differencing, ECMs and cointegration estimation of structural models gained a new perspective by eliminating the possible spurious relation in structural models.

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<sup>5</sup> Ron P. Smith (2002), “Unit Roots and all that: the impact of time-series methods on macroeconomics,” *Macroeconomics and the real world: Econometric Techniques and Macroeconomics*, Volume1.

<sup>6</sup> Katrina Juselius (2002), “Model and relations in economics and econometrics,” *Macroeconomics and the real world: Econometric Techniques and Macroeconomics*, Volume1.

<sup>7</sup> Ron P. Smith (2002), “Unit Roots and all that: the impact of time-series methods on macroeconomics,” *Macroeconomics and the real world: Econometric Techniques and Macroeconomics*, Volume1.

Box-Jenkins also brought a novel approach in time series models. In their framework, parsimonious equations, which were functions of their lagged values in autoregressive or moving average terms, were obtained by sufficiently differencing the series. The models, named as ARIMA models, are the simplest model for forecasting inflation. In these univariate linear models, inflation is forecasted as a function on its past values. Though these models may be useful for short-term forecasting, they may deviate from their point estimations in the long run since they don't take into consideration the relation of inflation with other variables in the economy. As a result, vector autoregressive (VAR) models were born as the second family of time series analysis for inflation forecasting. These models allow economists to measure the simultaneous (or joint) relation between the variables through the use of historical data.

Mainly, in VAR models, each dependent variable is regressed on lag values of itself and other variables in the VAR system. For example, if we have inflation and interest rates as the dependent variables in a VAR system (bivariate VAR equation), we first make regression of inflation both on its lag values and on the lag values of interest rates. Moreover, we also make regression of interest rate on its lagged values and on the lag values of inflation rates. However, while using a VAR regression in the aforementioned example, we have to first determine the lag length according to various lag length criteria tests as Akaike's information criterion (AIC) (Akaike 1973), Schwarz information criterion (SIC) (Schwarz 1978) Hannan-Quinn criterion (HQC) (Hannan and Quinn 1979), final prediction error (FPE) (Akaike 1969), and Bayesian information criterion (BIC) (Akaike 1979) etc...<sup>8</sup> Once the lag length is determined, then, we need to find out if there is a simultaneous relation between inflation and interest rates. With the use of Granger Causality Test (Granger 1969), we may discover the direction of the relation of the variables. This relation can be in neither, both or either direction. If the relation is in both directions, then, according to our example, inflation is said to Granger-Causal in respect to interest rate as well as interest rate is Granger Causal to inflation. As a result of this relation, we may use a VAR(p) (p stands as the lag length) model to forecast inflation. After the VAR system is obtained, we may use vector error-correction model (VECM) for the analysis of co integration in VAR models to ensure that the results are not an outcome of a spurious relation.

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<sup>8</sup> Venus Khim and Sen Liew (2004), "Which Lag Length Selection Criteria Should We Employ?," *Economic Bulletin*, Volume 2, Issue 33.

Though ARIMA and VAR models were useful in forecasting inflation, the lack of consideration of the non-linear structure of the variables in these models was one of the major drawbacks. ARIMA and VAR models mainly showed the general tendency of the inflation given the relation of the variables. However, they did not account for the asymmetric impact of economic shocks. In addition, with the emergence of recent evidences [Stock and Watson (1999)] showing the non-linear behavior of economic variables, non-linear modeling in time series gained importance in inflation forecasting.

The use of non-linear models is appealing because the economy of a country under consideration may go through differing periods that appear as structural breaks. These models are classified as regime switching models since they capture the asymmetry in economic shocks. The resulting regression equations of these models are obtained by the weighted average of the regime equations. Depending of the type of weighted averaging, such main non-linear models in the literature of inflation forecasts as Threshold Autoregressive Models (TAR), Smooth Threshold Autoregressive Models (STAR), Markov Switching Models, and Neural Networks help economists to study each period in its own time series property.

TAR models can be characterized as a piece-wise linear time series models<sup>9</sup>. That is, we may define a number of regime models with lag length  $p_i$  given the delay and the threshold parameters. For example, if we have the threshold parameter as equal to zero then we may create two-regime TAR model of order  $p_i$  given that the delay parameter is larger or smaller than the threshold parameter. In this way, we may capture the effects of negative or positive shocks to a selected dependent variable. However, the issue with TAR model is that the transition between the regimes is very strict, because the resulting regime switching equations are obtained through piece-wise weighted averaging. Thus, in order to smooth the strict transitional behavior of TAR models, STAR models are utilized. STAR models can be interpreted as a smoothly switching model between two extreme regimes according to the magnitude of the delay parameter<sup>10</sup>. This smoothly switching behavior is captured with the inclusion of a function (i.e. logistic function, exponential function).

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<sup>9</sup> Nobuhiko Terui and Herman K. van Dijk (2002), "Combined forecasts from linear and nonlinear time series models," *International Journal of Forecasting*, 18, pp. 421–438.

<sup>10</sup> Nobuhiko Terui and Herman K. van Dijk (2002), "Combined forecasts from linear and nonlinear time series models," *International Journal of Forecasting*, 18, pp. 421–438.

Markov Switching Models (Hamilton 1989) differ from TAR and STAR models in terms of the way it captures the distinct behavior of the regimes. In TAR and STAR models the transition among regimes are defined endogenously. That is the transition is gradual. However, in Markov Switching models regime switches are considered exogenous. The exogenous behavior among regime switches is captured by a probabilistic process. “That is, the probability of being in one regime depends on the state of a previous regime.”<sup>11</sup> Thus, the switches among regimes become a first order Markov Process. “In this way, the endogenously defined structural breaks in TAR and STAR models are left to inferences drawn on the on the basis of probabilistic estimates of the most likely state prevailing at each point in history. The estimates are done according to maximum likelihood techniques. Once the likelihood of each possible state is calculated then the probability that a particular state prevails is found by dividing the likelihood of that state by the total likelihood for both states. Usually a probability value larger than half percent indicates the occurrence of a particular state.”<sup>12</sup>

Artificial Neural Networks (ANNs) are also among non-linear techniques that recently gained ground in the inflation forecasting literature thanks to their ability to model complex non-linear patterns in a given data set. The main driver of ANNs can be summarized in its non-linear mapping structure for relationships that are difficult to fit. This is achieved by the inclusion of  $n$  different logistic functions ( $n$  hidden layers or nodes) along with a constant autoregressive term and time-varying coefficient in their structures. That is, if we have a highly non-linear data set, then we can obtain a functional outcome for the data through the proper selection of hidden layers in ANN. However, due to their structures ANNs have difficult economic interpretation. In addition, due to the large number of parameters (depending on the selection of the number of logistic functions) there is danger of overfitting the data. In order to prevent data overfitting, the number of hidden layers are selected according to Schwarz Bayesian Criterion (SBC). Once the number of parameters is determined, then the coefficients are estimated by recursive nonlinear least squares. However, “for these models, multiple local minima are an important concern, so the objective was minimized by an algorithm developed for this application. The algorithm uses a combination of random search methods and local Gauss-Newton optimization.”<sup>13</sup>

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<sup>11</sup> John Simon (1996), “A Markov-Switching Model of Inflation in Australia,” Reserve Bank of Australia, Economic Group, Research Discussion Paper 9611.

<sup>12</sup> John Simon (1996), “A Markov-Switching Model of Inflation in Australia,” Reserve Bank of Australia, Economic Group, Research Discussion Paper 9611.

<sup>13</sup> James H. Stock and Mark W. Watson (1998), “A Comparison of Linear and Nonlinear Univariate Models for Forecasting Macroeconomic Time Series,” NBER Working Paper 6607.

Other than utilizing linear and non-linear forecast models, combination of forecasting models are also utilized for forecasting inflation. The combination may be the outcome of either only linear or non-linear models or both. The main idea behind this approach is analogical to non-linear models. Most of the time, economic series perform differently under different regimes. The performance may be linear or non-linear given the condition of the economy during a relevant observation period. From the aforementioned case, it is evident that modeling inflation forecasts under a single regression equation might not always be the correct approach. Therefore, through the forecast combination of different models, it may be possible to obtain more robust results. The procedure for this technique starts with defining the forecast models that will be combined. Once the models to be combined are defined, then optimal weight is determined for each model according to an algorithm with the minimization objective of the error forecasts between the combined model and the forecast models.

In addition to econometric models surveys are also utilized for forecasting inflation. “Surveys sample households’, businesses’ and professional forecasters’ inflation expectations. They provide useful information on expectations and future behavior of economic agents.”<sup>14</sup> The Livingston Survey, the Survey of Professional Forecasters (SPF), the Michigan Survey, and European Commission’s Harmonized Consumer Survey are among the famous surveys showing the inflation expectations. Usually, survey results are the outcome of mean or median of the data obtain from professional forecasters or from the expectations of the household.

In sum, we have a large range of techniques from which we may forecast inflation. Each model may have its own advantages and disadvantages given the nature of the economy under study. Determining which model is the best approach to forecast inflation is a tedious task. New section gives the theoretical background of the statistical methods for model selection.

<p><i>General ARMA Models</i> (example: ARMA(<math>p, q</math>))</p>	$r_t = \phi_o + \sum_{i=1}^p \phi_i r_{t-i} + a_t - \sum_{i=1}^q \theta_i a_{t-i}$ <p>where <math>\sum_{i=1}^p \phi_i r_{t-i}</math> drive the AR process and</p> <p><math>\sum_{i=1}^q \theta_i a_{t-i}</math> drives the MA process.</p>
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<sup>14</sup> Jorge Ivan Canales-Kriljenko, Turgut Kışınbay, Rodolfo Maino, and Eric Parrado (2006), “Setting the Operational Framework for Producing Inflation Forecasts,” Central Bank of Chile Working Paper No 362.

<p><i>VAR Model</i> (example: Bivariate case)</p>	$r_{1t} = \phi_{10} + \Phi_{11}r_{1,t-1} + \Phi_{12}r_{2,t-1} + a_{1t}$ $r_{2t} = \phi_{20} + \Phi_{21}r_{1,t-1} + \Phi_{22}r_{2,t-1} + a_{2t}$ $r_t = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix}$ $r_t = \phi_0 + \Phi r_{t-1} + a_t$ <p>where <math>\Phi</math> is a <math>n \times n</math> matrix, and <math>\{a_t\}</math> is a sequence of serially uncorrelated random vectors with mean zero and covariance matrix <math>\Sigma</math>.</p>
<p><i>TAR Model</i> (Example: two regime TAR model with order <math>(p_1, p_2)</math>, denoted by <math>TAR(p_1, p_2; d, r)</math>.)</p>	$Y_t = \begin{cases} \beta_0^1 + \beta_1^1 Y_{t-1} + \dots + \beta_{p_1}^1 Y_{t-p_1} + \varepsilon_t^1 & \text{if } Y_{t-d} \leq r \\ \beta_0^2 + \beta_1^2 Y_{t-1} + \dots + \beta_{p_2}^2 Y_{t-p_2} + \varepsilon_t^2 & \text{if } Y_{t-d} > r \end{cases}$ <p>Where <math>\{\varepsilon_t^i\}</math> for <math>i=1, 2, \dots</math> is the innovation process with variances <math>\sigma_1^2</math> and <math>\sigma_2^2</math>. <math>d</math> is the delay and <math>r</math> is the threshold parameters.</p>
<p><i>STAR Model</i></p>	$x_t = c_0 + \sum_{i=1}^p \phi_{0,i} x_{t-i} + F\left(\frac{x_{t-d} - \Delta}{s}\right) \left( c_1 + \sum_{i=1}^p \phi_{1,i} x_{t-i} \right) + a_t$ <p>Where <math>d</math> is the delay parameter, <math>\Delta</math> and <math>s</math> are parameters representing the location and scale of model transition, and <math>F(\cdot)</math> is a smooth transition function. Usually <math>F(\cdot)</math> is considered a logistic, exponential or a cumulative distribution function. Mainly STAR is a weighted linear combination of the below two models:</p> $\mu_{1t} = c_0 + \sum_{i=1}^p \phi_{0,i} x_{t-i}$ $\mu_{2t} = (c_0 + c_1) + \sum_{i=1}^p (\phi_{0,i} + \phi_{1,i}) x_{t-i}$ <p>The weights are determined in continuous manner by the <math>F(\cdot)</math> function.</p>
<p><i>Markov-switching Model</i> (Example: two-state Markov-switching model.)</p>	$x_t = \begin{cases} c_1 + \sum_{i=1}^p \phi_{1,i} x_{t-i} + a_{1t} & \text{if } s_t = 1 \\ c_2 + \sum_{i=1}^p \phi_{2,i} x_{t-i} + a_{2t} & \text{if } s_t = 2 \end{cases}$ <p>The transition is driven by a hidden two-state Markov chain. <math>s_t</math> may take values in <math>\{1, 2\}</math> and is a first order Markov chain with probabilities: <math>P(s_t = 2   s_{t-1} = 1) = w_1</math> and <math>P(s_t = 1   s_{t-1} = 2) = w_2</math></p> <p>The innovational series <math>\{a_{1t}\}</math> and <math>\{a_{2t}\}</math> are sequences of i.i.d. random variables with mean zero and finite variance and are independent of each other. A small <math>w_i</math> means that the model tends to stay longer in state <math>i</math>, given that <math>1/w_i</math> is the expected duration of the process to stay in state <math>i</math>.</p>

<i>Artificial Neural Network Models</i>	$v_t = \beta_0' \zeta_t + \sum_{i=1}^{n_1} \gamma_{1i} g(\beta_{1i}' \zeta_t) + u_{t+h}$ (a single layer ANN) <p>where <math>g(z)</math> is the logistic function, <math>g(z) = \frac{1}{(1 + e^{-z})}</math>.</p> <p>When <math>y_t</math> is modeled in levels then, <math>y_{t+h} = v_{t+h}</math> and <math>\zeta_t = [1 \quad y_t \quad \dots \quad y_{t-p+1}]</math>. When <math>y_t</math> is modeled in differences <math>y_{t+h} - y_t = v_{t+h}</math> and <math>\zeta_t = [1 \quad \Delta y_t \quad \dots \quad \Delta y_{t-p+1}]</math>.</p> <p>If we would like to use two layers then we obtain ANN with two layers in the below form:</p> $v_t = \beta_0' \zeta_t + \sum_{j=1}^{n_2} \gamma_{2j} g\left(\sum_{i=1}^{n_1} \beta_{2ji} g(\beta_{1i}' \zeta_t)\right) + u_{t+h}$
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### 2.3.2- Model Selection Methods:

Forecast evaluation is an important task to carry out for model selection. It mainly consists of conducting an in-sample measure and then a pseudo out-of-sample measure. Through these measures forecaster assesses the accuracy of the models utilized.

As indicated in previous sections, inflation forecasts are conducted based on models that create causal relations between economic indicators and inflation. The aim of a forecaster is to capture the impact of the economic indicators on inflation through the regression models. Once the full-sample regression is run, a forecaster may obtain a list of explanatory variables that significantly predicts the pattern of inflation. In order to ensure the significance, the forecaster should refer to statistical measures and tests given in the regression results. Thus, an in-sample measure of a model consists of ensuring that the explanatory variables predict the inflation in accordance with economic intuition. This includes checking the significance and the stability of the coefficients of explanatory variables. These steps are important as the significance and stability validation may help the forecaster to build a robust inflation model.

Once the model is built then its predictive content should be checked. This can be done through a pseudo out-of-sample measure. A pseudo out-of-sample forecasting involves constructing inflation forecasts that a model would have produced had it been used

historically to generate forecasts of inflation<sup>15</sup>. Once a pseudo out-of-sample forecasts are generated their accuracy are compared with benchmark models. To quantify the comparison root mean square error (RMSE) or mean square forecast error (MSFE) measures are utilized. Once these measures are obtained then the ratio(s) of the candidate model(s) relative to a benchmark model is (are) computed. A ratio value less than 1 indicates that the candidate model(s) is (are) more accurate than the benchmark model.

In addition to the pseudo out-of-sample measure there are two additional complementary measures. These are forecast direction (M. Hashem Pesaran and Spyros Skouras 2002, McCracken and West 2002) and time distance criterion (Clive W.J. Granger, Yongil Jeon 2003). Forecast direction mainly involves measuring the ability of the model to forecast the direction of the inflation, and the time distance criterion measure the horizontal distance between the forecasted and actual series. The concept of horizontal distance is intuitive out of the assumption that the forecast lead the series being forecasted. For further details on these concepts the reader may refer to the aforementioned articles in this paragraph.

### **3- Literature Review:**

Inflation forecast studies with structural models may be largely attested to the estimation of generalized Phillips Curve (PC) models. The reason lays in the contingent evolution of PC models with relevant theories of macroeconomics. In their contingent evolution, PC models transitioned into more generalized forms by being compatible with various indicators. The generalization involved the departure from PC models' original format by including other alternative indicators as output gaps, indices, asset prices etc... and, in some studies, by combining their forecasts. At each step of the generalization, the attempts were made to increase the efficiency of inflation forecasts. Although their predictability is questioned by various studies, the forecast ability of PC models should not be underestimated as their use has been a reference point for many forecasts. As stated by Stock and Watson (1999), "as a tool for forecasting inflation, Phillips Curve is widely regarded as stable, reliable and accurate, at least compared to the alternatives."

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<sup>15</sup> Fisher, Jonas D. M., Chin Liu, and Ruilin Zhou, 2002, "When can we forecast inflation?," *Economic Perspectives*, Federal Reserve Bank of Chicago, First Quarter, pp. 30–42.

In his seminal 1958 paper, A.W. Phillips presented the Phillips Curve as the outcome of the inverse relation between money wage changes and the unemployment rate in the British Economy over the period from 1861 to 1957. In 1960, Paul Samuelson and Robert Solow transformed PC into an inverse relation between wage inflation and unemployment rate. After this transformation, PC was extensively utilized to explain and forecast inflation. However, the failure of this form in explaining the stagflation in the late 1960s and 1970s, led to the presentation of a new PC model by monetarist economists such as Milton Friedman and Edmund Phelps. The name for the new form was expectations-augmented PC, where PC was transformed into a price inflation equation. This new form also led the birth of non-accelerating inflation rate of unemployment (NAIRU) terminology which appeared as a vertical line in the PC figure if inflation is fully anticipated. That is, though PC still keeps the inverse relation between unemployment and inflation in the short-run, it becomes vertical in the long run because there could only one single rate of unemployment rate with a given stable inflation rate. Within this assertion, NAIRU appeared as a type of new natural rate of unemployment, and, inflation is forecasted based on the difference between the NAIRU and the actual unemployment rate (unemployment gap); if actual unemployment is below NAIRU then inflation increases. According to rational expectations theory any policy to decrease unemployment below NAIRU would cause inflationary pressure which leads expectations of inflation to increase. Increasing inflation expectations would in turn cause the failure of the policy. Thus, given the new form of the PC any movement away from stable NAIRU would lead to policy failures in the long run (Phelps, 1967; Friedman, 1968; Lucas, 1972a, 1972b, 1973).

The NAIRU concept is based on the earlier theories of new classical economists. In their causal formulation (based on the Quantitative Theory of Money) of inflation with money supply, monetary economists governed the thesis in line under the famous dictum of Friedman (1977): “inflation is always and everywhere a monetary phenomenon”. That is, an excess supply of money would cause aggregate demand to increase, which, in turn, would result in increasing inflation. Within this framework, the money supply-inflation causality under the continuous market clearing and imperfect information assumptions shed the light to the birth of rational expectations (RE) theory. This approach, highly influenced by the work of Lucas (1976) (Econometric Policy Evolution: A Critique), challenged that Keynesian models were not useful for policy analysis. Further, Lucas (1973), through its new business cycle theory, suggested that a successful policy depends to the extent which it surprises people. Along with

Lucas views, other influential studies at the time (Barro, 1977; Sargent & Wallace 1975) led the new formation of PC, hence the birth of NAIRU concept.

Another wave of new classical economists, named as business cycle (RBC) theorists (Kylas and Prescott, 1982; Long and Plosser 1983), studied the impact of supply shocks to business cycle under the assumptions of their earlier classical economists. Thus, beside the demand pull factors, “the emphasis switched to the role of random shocks to technology and the intertemporal substitution in consumption and leisure that these shocks induced”<sup>16</sup>. In essence, the studies of RBC theorists mainly shed light to the effects of supply shocks to inflation.

Although new classical economists brought a more rigorous view to macroeconomics in their microeconomics analyses, their assumptions were challenged by the studies of the New Keynesian economists. “The new classical economists ignored the possibility of adjustment lags which may stem from rigidities in wages and prices in the short run. New Keynesians have investigated the possible microeconomic causes of these rigidities to eliminate the Keynesian arbitrary assumption of fixed wages and prices in the short run. According to the studies (Fischer, 1977 ; Taylor, 1979, 1980 ; Rotemberg, 1982 ; Calvo, 1983 ; Mankiw, 1985 ; Akerloff and Yellen, 1985 ; Blanchard and Kiyotaki ,1987 ; Ball and Romer,1990) of new Keynesians, wage and price stickiness in the short run can be explained by factors like small menu costs or staggered wage and price changes.”<sup>17</sup> Thus, according to new Keynesian views the time path of inflation may also be affected by possible inertial factors in the economy.

One of the main important reasons<sup>18</sup> for the studies of new Keynesians may also be attested to the expanding US Economy during 1990s. These studies shed light not only to the birth of New Neoclassical Synthesis (NNS)<sup>19</sup> but also to the investigation of unstable NAIRU and the new forms (generalized) of Phillips Curve models.

During 1990s there had been a debate whether NAIRU became unstable since the inflation stayed very moderate when the actual unemployment rate fell below 4% of the labor force. In early 1990s, the studies of macro variables within PC framework of Motley (1990) and

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<sup>16</sup> N. Gregory Mankiw (2006), “The Macroeconomist as Scientist and Engineer”.

<sup>17</sup> Kibritcioglu, A. (2002): “Causes of Inflation in Turkey: A Literature Survey with Special Reference to Theories of Inflation,” *Inflation and Disinflation in Turkey*, ed. By Kibritcioglu, A., L. Rittenberg, and F. Selcuk, Aldershot: Ashgate, pp. 43-76

<sup>18</sup> See N. Gregory Mankiw (2006), “The Macroeconomist as Scientist and Engineer”.

<sup>19</sup> See Goodfriend and King (1997), Clarida, Gali, and Gertler (1999), McCallum and Nelson (1999), and Michael Woodford (2003).

Weiner (1993) suggested that NAIRU has increased. On the other hand, Tottell (1994)'s examination of PC suggested little support for the increase of NAIRU and that it fluctuates around the historical estimate of 5.7%. Moreover, Fuhrer (1995) documents that the PC shows a remarkable stability over a period of 35 years with his empirical study. However, Gordon (1997, 1998) and Staiger, Stock and Watson (1997a, b) finally showed the instability and decline of NAIRU. The main motivation behind unstable NAIRU was that the US economy has changed since 1980s due to the higher volatility in business cycle, monetary policy and inflation rate. As a result, a further new form of PC was born.

This new form can be interpreted under triangle model of inflation [Gordon 1997]. According to this model, the actual inflation rate was determined by three determinants which are short-term Phillips Curve Inflation (demand), supply shocks and inertia. The idea of the new form was that the drivers behind the shifts of the short-run PC are supply shocks and inflation inertia. Thus, PC is represented only by the demand determinant of the triangle model. In this presentation payroll growth was related to inflation rate under “a model of staggered nominal price setting by monopolistically competitive firms”<sup>20</sup>.

This new form also explains the unstable, hence time varying, nature of NAIRU. Because of this unstable nature, inflation forecasts based on unemployment figures became a challenging issue for econometricians. As a result, more generalized formats of PC were undertaken for forecasts to find new and more stable predictors; “Staiger, Stock, and Watson (1997a) considered 71 candidate leading indicators of inflation, both financial and non-financial (quarterly, U.S.), and in a similar but more thorough exercise, Stock and Watson (1999b) considered 167 candidate leading indicators (monthly, U.S.). They found a few indicators that have been stable predictors of inflation, the prime example being the capacity utilization rate. Gordon (1998) and Stock (1998) confirmed the accuracy of recent U.S. inflation forecasts based on the capacity utilization rate. Stock and Watson (1999b) also suggested an alternative Phillips-curve-type forecast, based on a single aggregate activity index computed using 85 individual measures of real aggregate activity”<sup>21</sup>.

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<sup>20</sup> Jeannine Bailliu, Daniel Garcés, Mark Kruger, and Miguel Messmacher (2003), “Explaining and Forecasting Inflation in Emerging Markets: The Case of Mexico”, Bank of Canada Working Paper 2003-17.

<sup>21</sup> James H. Stock and Mark W. Watson (2003), “Forecasting Output and Inflation: The Role of Asset Prices,” *Journal of Economic Literature*, Vol XLI 41, pp. 788-829.

Although new alternatives were developed, studies that test the reliability of PC based forecasts continued. For example, the recent article of Andrew Atkeson and Lee Ohanian (2001) challenged the reliability of alternative PCs for forecasting inflation. In their study, Andrew Atkeson and Lee Ohanian found that neither the unemployment- based nor the activity index–based NAIRU Phillips curve inflation forecasts studied by Stock and Watson (1999a) have been substantially more accurate than a naïve (random walk) forecast since 1984<sup>22</sup>. In addition, the studies of Cecchetti, Chu and Steindel (2000), and Sims (2002) found that PC model based forecasts are particular to their sample periods. Also, Clark and McCracken (2003) showed the effect of the instability of the output gap coefficient in a PC model for forecasting inflation. IMF (1996), in turn, showed that the output gap did not play an important role in emerging market economies.

On the other hand, Fisher, Liu, and Zhou (2002)<sup>23</sup>, and Stock and Watson (2003)<sup>24</sup> presented new approaches by addressing the issues with the above studies. Fisher, Liu, and Zhou argued that the findings of Atkeson and Ohanian (2001) may have been particular due to the special features of the sample period they have worked for. To prove this point they considered three distinct periods (1977-1984; 1985-1992; 1993-2000) by adding core personal consumption expenditures deflator (PCE) to the list of inflation measures along with CPI and CPI less energy and food components. In addition they utilized a broader class of Stock and Watson (1999b) type models. Fisher, Liu and Zhou’s findings confirm the Atkeson and Ohanian results for the 1985-2000 results, but not for 1977-1984. They showed that PC models perform poorly both for 1985-1992 and 1993-2000 periods while forecasting core CPI. On the other hand, for PCE forecasting, PC models perform better than naïve (random walk) model forecasts during the 1993-2000 period. Furthermore, they found that, while PC models do poorly for forecasts with one year horizon, these models perform better than naïve models for forecasts with two year horizon at least for core inflation measures. In sum, they concluded that the periods of low inflation volatility and periods after regime shifts favor naïve models. However, in their assertion, although PC models fail to give strong results for the magnitude of inflation due to structural breaks, they perform relatively well in forecasting the direction of inflation.

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<sup>22</sup> Andrew Atkeson, Lee E. Ohanian (2001), “Are Phillips Curves Useful for Forecasting Inflation?,” *Quarterly Review*, Federal Reserve Bank of Minneapolis, Vol. 25, No. 1, Winter, pp. 2–11.

<sup>23</sup> Fisher, Jonas D. M., Chin Liu, and Ruilin Zhou, 2002, “When can we forecast inflation?,” *Economic Perspectives*, Federal Reserve Bank of Chicago, First Quarter, pp. 30–42.

<sup>24</sup> James H. Stock and Mark W. Watson (2003), “Forecasting Output and Inflation: The Role of Asset Prices,” *Journal of Economic Literature*, Vol XLI 41, pp. 788-829.

Similar conclusions can also be inferred from the study of Stock and Watson (2003). The inference may be laid in the hypothesis that selecting a single model for multiple periods may lead to erroneous conclusions since there are structural breaks in the economy. Staying in line with the aforementioned conclusion, Brave and Fisher (2004) showed that a robust forecast of the magnitude of inflation can be obtained by combining the forecasts of several models that incorporate the information in the available data in different ways<sup>25</sup>.

In sum, the empirical failure of 1960s PC, debate over NAIRU and reliability of structural models based on PC drove attention to alternative studies on forecasting inflation. The aim was to obtain more efficient results by finding new indicators. The studies under this aim extensively utilized time series models with financial indicators (or asset prices). The motivation behind using financial indicators was that their values were obtained through a discounting process of their expected values. Furthermore, another motivation was that interest rates may contain useful information of expected inflation rate according to Irving Fischer's theory. Thus, financial indicators may have information about future economic developments that may impact the foundations of macroeconomics.

Most of the forecast studies done through the use of financial variables sought to identify the relation of inflation with interest rates, term structure, default spreads, stock prices, exchange rates, commodity prices, housing prices etc...

The early studies with financial indicators can be mainly traced back to the models that involve interest rates as the predictor on inflation rates. Mainly, the short term interest rates are found to have a predictive content for forecasting inflation. "The early study of Fama (1975) shows that an interest rate model, in which expected real returns on treasury bills are constant through time, provides good inflation forecasts for the 1953-71 period. Another study by Fama and Gibbons (1982) also found that, when expected real returns are assumed to follow random walks, Treasury bill rates provide good inflation forecasts for the entire 1953-1977 period"<sup>26</sup>. Furthermore, based on the US data and on his VAR study, Sims (1980) found that the commercial paper rates have predictive content for inflation.

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<sup>25</sup> Scott Brave and Jonas D. M. Fisher, 2004, "In search of a robust inflation forecast," *Economic Perspectives*, Federal Reserve Bank of Chicago, Fourth Quarter, pp. 12-31.

<sup>26</sup> Eugene F. Fama, Michael R. Gibbons (1984), "A Comparison of Inflation Forecasts," *Journal of Monetary Economics*, 13, pp. 327-348.

The following studies mainly study the predictive power of the term spreads on inflation. The relation between term spreads and inflation may be attested to the expectations hypothesis of term structures. According to this theory, the forward rates (expected rates) obtained from term structure may contain information for future inflation. However, a large number of studies found little or no predictive content in the term structure of nominal interest rates for forecasting inflation. In his series of papers Mishkin (1990a, b) utilized the term structure of US government bonds to test the predictive content of the term spread on inflation. He found that the short end (maturities with six months or less) of the term structure of nominal interest rates had no predictive power for the future path of inflation. However, Mishkin (1990b) found predictive content for the long end of the term structure. For longer maturities of nine and twelve months, the term structure of nominal interest rates provided information for the future path of inflation.

Similar conclusions are supported by Jorion and Mishkin (1991)'s and Mishkin (1991)'s cross country study. Jorion and Mishkin (1991) found that term structure did have strong predictive ability to forecast inflation at long maturities for Britain, West Germany, and Switzerland. In addition, Mishkin (1991) found that out of ten OECD countries only in three countries, the term structure of nominal interest rates had predictive content. Further studies included the predictive ability of term structures on inflation for Germany. Gerlach (1997), Davis and Fagan (1997), Estrella and Mishkin (1997) applied variations of the rational expectations and Fischer Hypothesis to show that the term structure included predictive content for future inflation for maturities of or over three years in Germany. In addition, the study of Davis and Fagan (1997) for a group of developed economies in Europe shows also that only a small number of spreads contain predictive information, and improve forecasting in a manner which is stable over time<sup>27</sup>.

In his previous regression studies, Mishkin utilized only the term spreads with no lags. However, the study of Estrella and Mishkin (1997) utilized a single lag of inflation in the regression equation to control the lagged inflation and to test the predictive content of term spread in this format. They found that the predictive content of term spread is significantly reduced when a single lag of inflation is added. Within this framework, Kozicki (1997) found

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<sup>27</sup> Davis, E Philip, Fagan, Gabriel (1997), "Are Financial Spreads Useful Indicators of Future Inflation and Output Growth in EU Countries?," *Journal of Applied Econometrics*, vol. 12, issue 6, pages 701-14.

that the term spread had predictive content for inflation at one year horizon in only two of the ten OECD countries. Furthermore, by adding lagged value of inflation Bernanke and Mishkin (1992) also found little or no predictive content of term structure for future inflation in six major economies. However, Barr and Campbell (1997) showed that the implicit inflation expectation obtained through the spread between forward rates of nominal term structure and British index-linked bonds had predictive content for forecasting inflation.

Inflation forecasts are also conducted based on the predictive content of default spreads and probability of default. A default spread is the difference between the term structures of a private debt (i.e. corporate bonds) and government debt at a certain maturity. Probability of default is the likelihood that an agent will fail to meet its debt obligation under a default event. Friedman and Kuttner (1992) found little predictive content of the paper-bill spread for inflation using Granger Causality tests<sup>28</sup>. A further study was conducted by Blanchard (2004) on the basis of probability default. In his paper he aimed showing the perverse effects of the interest rates on exchange rates and inflation. “Through the use of Brazilian data, he found that an increase in the real interest rate in response to a higher inflation led to a real depreciation because of increasing credit risk (default probability). A real depreciation in turn led to a further increase in inflation”<sup>29</sup>.

Some of the studies for finding the predictive content of stock prices for forecasting inflation are done under the model of Fischer hypothesis. Most of the studies (Bodie, 1976; Jaffe and Mandelker, 1976; Nelson, 1976; Fama and Schwert, 1977) done for the US data found negative relation between inflation rate and stock market concluding that Fischer hypothesis does not hold in the stock market.<sup>30</sup> Through the use of Livingston survey of expectations data, Gultekin (1983) concluded that Fischer Equation hold much better for *ex ante* expectations than for *ex post* realizations and that the expected real returns on common stocks were positively correlated with expected inflation. He also found similar results in his previous study (Gultekin, 1983) over twenty-six countries during post-war period. He concluded that Fischer Equation did not hold implying the consistent positive lack of relation between stock prices and inflation. A further study conducted through an international data set

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<sup>28</sup> James H. Stock and Mark W. Watson (2003), “Forecasting Output and Inflation: The Role of Asset Prices,” *Journal of Economic Literature*, Vol XLI 41, pp. 788-829.

<sup>29</sup> Olivier Blanchard (2004), “Fiscal Dominance and Inflation Targeting. Lessons from Brazil,” Working Paper 04-13.

<sup>30</sup> N. Bulent Gultekin (1983) , “Stock Market Returns and Inflation Forecasts,” *The Journal of Finance*, Vol. 38, No. 3, pp. 663-673.

by Goodhart and Hofmann (2000a) found that stock prices did not have any predictive content for inflation.

Other studies with financial indicators involve the use of commodity prices, exchange rates, housing, etc... as the indicators to predict inflation. Stock and Watson (1999) found that the commodity prices did not improve the inflation forecasts at one year horizon in the search for alternative indicators to their generalized PC models. In addition, Boughton and Branson (1988), and Baillie (1989) showed that there was no relationship with commodity prices and CPI. Furthermore, Pecchenino (1992) showed the reason why commodity prices were not a useful predictor for inflation forecasts through an adaptation of Fisher-Gray model of long term contracts. On the other hand, Robert Gordon (1982, 1998) found that exchange rates had predictive power for US inflation in his in-sample test. In terms international case, Goodhart and Hofmann concluded that the use of exchange rates and lagged inflation for inflation forecasts produced more efficient results than a simple autoregressive forecast in only one or two of the seventeen countries. For housing, Stock (1998) and Stock and Watson (1999b) found that housing prices had predictive power for inflation in the United States. Furthermore, Goodhart and Hofmann (2000b) found that housing prices are significant in predicting inflation rates in seventeen OECD countries. The main idea behind these studies was that housing takes a large part in the wealth of many nations, and it has thus a considerable share as a component in CPI.

Finally, Stock and Watson (2003)'s study showed to predict new financial predictors for forecasting inflation and output that asset prices have a stronger predictive power for output growth and that forecasts based on individual indicators are unstable. However, they found that forecasts based on combinations of the information in the various predictors seemed to avoid the worst of the instability problem. In conclusion, they asserted that the challenge for future studies is to find models that take into consideration the evolving nature of predictive relations.

Beside the search for new indicators, there have also been considerable attempts to find more robust models for forecasting studies. These studies mainly involve the work with atheoretical time series models. In these models, the aim was to capture simultaneous relations, structural breaks, and non-linearity in economic environment. It should be noted that, most of the aforementioned studies utilized atheoretical models in some forms (i.e. Sims (1980)'s VAR

study). However, there is also a range of other time series studies that heavily used new techniques to forecast inflation. The aim is to highlight these studies with their advantages and disadvantages.

Through their study Stockton and Glassman (1987) showed that a simple ARIMA model of inflation provided better forecasts than theoretical macro models as monetary model, rational expectation model and expectations augmented PC model. However, they did not take into account term structure models in the comparison. They concluded their paper by stating that “theory has yet to yield only small dividends in terms of improving our ability to predict accurately the course of inflation”. Though new theoretical models were on the course of development at the time, the gap in theoretical forecasting is turn led more intense use of time series models. Under the future will be like the past assumption the performance of these studies were evaluated most of the time based on a benchmark ARIMA model or as shown previously on a naïve inflation model.

Most of the early studies in this are were based on the use of VAR models. The reason was to capture the simultaneous relation of inflation with candidate economic indicators. Furthermore, VARs make a connection of structural models to reduced form forecasting models in a flexible way. Especially, after the work of Sims (1980b), VAR studies became popular among the economists of last twenty years or so<sup>31</sup>. Given this popularity, to evaluate VARs’ forecast performance Webb (1984) compared a simple VAR model with a structural model of a major consulting firm, and with a series of consensus forecasts. In this study, he found that post-sample predictions of VAR models did well compared to other methods in the study and that only VAR model predicted the 1982 recession. Hakkio and Moris (1984) asserted that, although VAR models could not be used to make inferences on the structure of an economy, they could be used to approximate a reduced form model that can also be derived from the structure of an economy. They also provided the empirical evidence that a VAR model could be superior to a structural model that was incorrectly specified. In addition, Webb (1985) provided the evidence that forecasts based on VAR models could be improved by restricting the parameterization of VAR models. Though the improvement was not large, it was consistent. Further, Lupoletti and Webb (1986) showed that a simple VAR model was a good benchmark for predictive accuracy since their VAR model produced competitive

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<sup>31</sup> Dharmendra Dhakal, Magda Kandil, Subash C. Sharma, and Paul B. Trescott (1994), “Determinants of the Inflation Rate in the United States: A VAR Investigation,” *The Quarterly Review of Economics and Finance*, Vol. 34, No. 1, pp. 95-114.

forecasts with those of ARIMA and Bayesian VAR model. They also showed that combining VAR model forecasts with those from a commercial forecasting service resulted in more efficient model, since VAR forecasts contained information that were missed by the models of commercial forecasting services.

The use of VARs was, however, challenged (especially Sims (1980)'s approach) by the studies of Cooley and LeRoy (1985), and Learner (1985). They conceded that the use of VARs without making structural assumption would create identification issue because the economic interpretations of the impulse response functions may not be reliable due to missing structural assumptions. By agreeing with this point, Sims (1986) and Bernanke (1986) created a VAR model that takes into consideration the structural assumptions. The new model was called structural-VAR (SVAR). SVARs basically require identifying restrictions while improving the structural parameters through an estimation algorithm. Thus, in SVARs, the extent to which specific innovations were allowed to affect some subset of variables, either in the short-run or in the long-run, is derived explicitly from structural macroeconomic models<sup>32</sup>. In short, SVARs use economic theory to sort out the contemporaneous links among the variables<sup>33</sup>.

Another problem with the use of VAR models was the tradeoff between oversimplification and overparametrization. Litterman (1985) showed that a Bayesian approach (BVAR) can balance this tradeoff by giving improved pseudo out-of-sample forecasts.

Though there have been considerable improvements in VAR models, inflation forecasts with VARs were comparatively weaker. McNees's data shows that the average error of the series of Litterman's inflation forecasts was typically the worst of several that were compared with his errors often double those of the best forecaster<sup>34</sup>. To improve inflation forecasts with VARs, Webb (1994) offered the addition of a dummy variable or dividing the entire sample into three subperiods to capture the structural breaks in the economy. In this way, Webb was able to capture the changing regimes during the post-war periods. In addition, he found that the changes in monetary policy were the main driver behind the large and relentless changes in

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<sup>32</sup> Pierre-Daniel G. Sarte (1997), "On the Identification of Structural Vector Autoregressions," *Economic Quarterly*, Federal Reserve Bank of Richmond, Volume 83/3, Summer, pp. 48-68.

<sup>33</sup> James H. Stock, Mark W. Watson (2001), "Vector Autoregressions," *The Journal of Economic Perspectives*, Vol. 15, No. 4, pp. 101-115

<sup>34</sup> Roy H. Webb (1994), "Forecasts of Inflation from VAR Models," Federal Reserve Bank of Richmond Working Paper 94-8.

inflation rates. This conclusion was also partially confirmed in the article of Dhakal, Kandil, Sharma, and Trescott (1994). They found in their VAR study that changes in the money supply, the wage rate, the budget deficit and energy prices were significant determinants of the inflation rate in the United States.

A further study by Stock and Watson (2001) utilized three VAR models with three variables: reduced form VAR, recursive VAR, and structural VAR with inflation, unemployment and interest rates. After defining the comovements among three variables with the use of reduced form VAR and recursive VAR, they used recursive VAR for forecasts. They found that forecasts from their recursive VAR model improved upon the forecasts of both the autoregressive and random walk models. Once the forecasts were done, they utilized structural VAR to make their economic interpretation (policy analysis) of the contemporaneous correlation among the variables. They showed that inference with structural VARs was not an easy task; the inferences from VAR results are mainly conducted upon the evaluation of impulse response functions. In the impulse response functions, VAR shocks reflect omitted variables that might be correlated with the included variables. If this is the case, then the estimates will contain omitted variable bias. This, in turn, may result in bizarre causal relations in impulse response functions. Thus, while analyzing VAR results it is important to make a clear distinction between reduced form VARs and structural VARs.

Finally, Bachmeier and Swanson (2003), in terms of comparison between VAR in difference and VEC models, suggests that imposing a cointegration relation to money, output and prices yields a better inflation forecasting performance than that of the variety of other forecast models including VAR in differences and a version of the Phillips curve. However, when cointegration relation is estimated rather than imposed, VEC models forecasts are found to be always much worse than VAR in differences forecasts. This conclusion is also empirically proven through a Monte Carlo simulation.

In international case, Canova (2002) through a study based on G-7 countries suggests that the simplest and most naïve don't always produce better inflation forecasts. In addition, forecast models based on generalized PC models and other small scale specifications are not better than univariate ARIMA models in several of the countries. However, multivariate models as VARs and BVARs with time varying coefficients and some international linkages produce better forecasts than univariate models with either constant or time varying coefficients.

Especially, adding a Bayesian prior improves the forecasts of VAR models. Furthermore, the article of Holden and Broomhead for modeling UK inflation suggests that the poor forecasts performances of unrestricted VAR models can be improved with the use of BVAR models. However, they note that their models do not utterly exploit the time series property of the data.

Further studies in the area of time series forecasting of inflation involve the use of Markov-switching and Neural Network models. Markov Switching Model is mainly used to capture the impact of different regimes to inflation. By identifying the shifts in inflation through a Markov-switch model for the post war period, the study by Evans and Lewis (1995) analyzed the long run relation between inflation and interest rates. In conclusion, they were not able to reject the null hypothesis of the long run one-to-one relation between inflation and nominal interest rates as stated in Fisher's hypothesis. Another study conducted, via the expectations augmented Markov-switching Phillips Curve as a measurement equation, by Guerrero and Million (2004) found that dynamics of inflation changed across regimes. That is, while a Keynesian Regime was identified for the period 1973-1983, the last twenty years was identified with a classical regime where economic agents have rational expectations and where unemployment rate was close to its natural level. Beside the studies for the US case, the studies of Simon (1996) and Ivanova, Lahiri, and Seitz (2000) involve the international case. Through his study for modeling Australian Inflation since the early 1960s, Simon (1996) found that Markov-switching models proved to be a useful supplement to the conventional models of inflation. His results indicated that the two-switch regime specification performed successfully by indicating regime changes in early 1970s and 1990s. This, in turn, suggests that the change for forecasting rule could be conducted occasionally. Furthermore, each regime could be modeled with a simple autoregressive model that includes the information on the output gap.

Ivanova, Lahiri, and Seitz (2000) studied the relative performance of interest rate spreads as predictors of German inflation and business cycle in the post-Bretton Woods era. Through their the two-regime Markov-switch model they found that yields were good predictors of inflation and business cycles since the model allowed the dynamic nature of the economy to change between expansion and recession.

Neural Network models are used in a series of papers to forecast inflation. Within this framework, these studies tried to model the complex non-linear nature of economic variables to obtain more robust forecasts. Moshiri and Cameroni (1998)'s study compared the performance of Back-Propagation Artificial Neural Network (BPN) model with such traditional models as a structural reduced form model, an ARIMA model, a VAR model and a BVAR model. After comparing the performances based on root mean square errors and mean absolute errors with horizons of one, three and twelve months, they found that BPN models forecasted inflation equally well or better than the traditional models. The performance of Neural Network models is also confirmed by the findings of McNelis and McAdam (2004) and Nakamura (2005). McNelis and McAdam (2004) forecasted inflation with linear and neural network models that are based on Philips Curve formulations in the USA, Japan and the Euro Area. They called their neural network model "thick" model in such a way that thick models' forecasts represent the trimmed mean forecasts of several neural network models. To measure the performance of thick models, they used well performing linear models as the benchmark. In conclusion, they found that Phillips Curves specification based on thick models were competitive with the linear specification. However, when it comes to service sector indices of the CPI for the euro area, they found that thick models performed equally well or better than linear models based on real time and bootstrap forecasts. The findings of Nakamura (2005) also show that neural network based inflation forecasts performed better than those of AR models for horizons of one and two quarters during the period 1978-2002.

In addition to using time series models, forecasters also tried to combine various models to obtain more robust inflation forecasts. Some of these studies were discussed previously (i.e. Brave and Fisher, 2004). The motivation was to reduce the errors and capture any time series property missed by the solitary models of inflation forecasts. Engle, Granger, Kraft (1984) used a bivariate generalization of Engle's ARCH model to combine a stylized monetarist model and a markup model for forecasting US inflation. ARCH model was utilized to find the optimal combination of time varying weights. In the end, they found that time varying combination of the models did not improve the forecasts results of fixed weight combination model. However, they asserted that using a time varying weight schedule "could bring one closer to describing the true data generation process"<sup>35</sup>. In terms of international evidence,

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<sup>35</sup> Robert F. Engle, C.W.J. Granger, and D.F. Kraft, (1984) "Combining competing forecasts of inflation using a bivariate ARCH model," *Journal of Economic Dynamics and Control*, 8, pp. 151-165.

Holden and Peel (1988a) combined UK inflation forecasts of six forecasting organizations and analyzed the accuracy of combinations along with the mean forecasts. They concluded that the forecasts of the optimal combination are inferior to the simple mean of the forecasts. Thus, the optimal combination should not be used since the forecast mean of the solitary models performed well. On the other hand, Rhim, Khayum, Schibik (1994) compared the performance of a composite forecast of inflation with the forecast performance of four different methods (a survey of professional forecasters by ASA and NBER, a random walk inflation model, ARIMA model, Fisher model). They found that a composite forecast of inflation improved upon the performance of the four models. Additional evidence on robust performance of combination models were evidenced by Jacobson and Karlsson (2002) of Svergies Risk Bank and by Kapetanios, Labhard, and Price (2006). By considering a Bayesian Model Averaging to specify indicator models for Swedish inflation, Jacobson and Karlsson (2002) found that combining the top ten leading indicator models yielded more robust inflation forecasts through smaller root mean squared errors. Furthermore, Kapetanios, Labhard, and Price (2006) found that the predictive likelihood model averaging (PLMA) technique to pseudo out-of-sample UK inflation forecasting performance of various models help the resulting combination model to beat a benchmark AR model most of the time. In addition, they also found that PLMA also did better than Bayesian model averaging, information theoretic model averaging, and equal weight model averaging.

Other than combining forecasts of various models, surveys are also used to forecast inflation. Mainly, the studies conducted with surveys involved finding whether surveys or time series models are better predictors of future inflation. That is, the findings from surveys and time series models are compared and the results were generally evaluated in favor surveys. A recent article by Ang, Bekaert, and Wei (2005) gives a literature over the comparison of survey methods with other methods. The article also examines the inflation pseudo out-of-sample forecast performance of four common methods: ARIMA models, real activity measures of Phillips Curve, term structure models that include linear, non-linear and arbitrage free specifications and survey based measure. Furthermore, they also examined the performance of optimal combination of forecasts. While mentioning previous studies that compared survey based measures with other methods, Ang, Bekaert, and Wei also show the lack of general comparison in these studies. For example, Fama and Gibbons (1984), while comparing Livingston Survey with the term structure forecasts, did not take into account the forecasts from macro variables. In addition, Grant and Thomas (1999), Thomas (1999) and

Mehra (2002) only utilized time series models to compare pseudo out-of-sample performance of survey measures. However, they did not consider Phillips Curve models or term structure models. Thus, according to Ang, Bekaert, and Wei, “the lack of a study comparing the four methods of inflation forecasting implies that there is no well-accepted set of findings regarding the superiority of a particular method”<sup>36</sup>. To overcome this deficiency, they did an extensive study, which, in conclusion, found that survey measures outperformed the other forecasting methods and that term structure specifications performed poorly. They also found little evidence that the performance of combined forecasts (from median, mean and optimal weights) outperformed that of survey measures. Further, they stated that survey information was consistently given the largest weight while combining forecasts, other methods had little weights in combined forecasts compared to survey information.

Conclusion on the better performance of surveys was also previously found by Hafer, Hein (1985). They compared the mean survey measures of American Statistical Association-National Bureau of Economic Research survey with a univariate time series model and an interest rate model based on the methodology of Fama and Gibbons (1984). They found that the inflation (based on GNP deflator) forecasts of survey outperformed those of other models. Thomas (1999) also found that consensus inflation forecasts of both economists and household performed better than the naïve and Fisher Hypothesis based inflation forecasts. However, he suggested that survey measures were biased; survey forecasts have different outcomes in an increasing and decreasing inflation rates. That is, surveys tend to overestimate inflation when inflation is decreasing and underestimate inflation when inflation is increasing. As Thomas stated these findings imply that, “inflation does have important redistributive consequences over lengthy horizons and the biased nature of survey results provide no support to the view that monetary policy is rendered ineffective as a result of the behavior of economic agents”<sup>37</sup>.

Through adjusting the survey results for bias, Ang, Bekaert, and Wei (2005) still concluded that survey based forecasts outperformed other methods in the article. However, it should be noted that most of the results of surveys are the outcome of the forecasts from professional forecasters (with the exception of Michigan survey based on household expectations).

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<sup>36</sup> Andrew Ang, Geert Bekaert, Min Wei (2005), “Do Macro Variables, Asset Markets Or Surveys Forecast Inflation Better?,” NBER Working Paper 11538.

<sup>37</sup> Lloyd Thomas B. Junior (1999), “Survey Measures of Expected US Inflation,” *The Journal of Economic Perspective*, Vol.13, No.4, pp. 125-144.

Because these surveys give the mean or median of the responses, they may be in turn considered as the combination of different methodologies for forecasting inflation. As a result, the so claimed superiority of surveys may be dependent on the aforementioned time series or structural techniques. This dependence thus should be a shield against the assertion that surveys are better predictors for inflation forecasts and those professional forecasters should rely on survey results rather than developing complex time series models.

#### **4- Predictors of Inflation in Emerging Markets and Turkey:**

As mentioned in the literature review section, the causes of inflation are generally studied under demand-pull, cost-push and monetary approaches. In emerging market case, these approaches mainly concentrated on nominal exchange rates, fiscal imbalances, central bank independence, and inertial inflation for explaining the inflationary process.

Monetary based approaches of inflation rely on the consensus that inflation is a monetary phenomenon in the long run. However, monetary approaches for the analysis of inflation should be used with caution as financial innovation and short-run elasticity of money may bring instability to the money-inflation relation. But, at the end monetary approaches are good for the analysis of inflation in the long run. According to this approach, the monetary disequilibrium (measured with monetary gap=money supply-money demand) as a result of excess money may transmit to higher inflation by increasing the aggregate demand in the long run. Thus, an excess supply of money can translate into inflationary pressure in much the same way that an excess demand for goods does; too much money chases too few goods<sup>38</sup>. In emerging markets, the reason for excess money may be attested to fiscal imbalances that may arise from the lack of well developed tax collection system, weakness of regulatory institutions, limited access to foreign borrowing and political instability are stated as the main factors behind budget deficits and thus behind inflation (Catão and Terrones, 2001; Bailliu, Garcés, Kruger, and Messmacher, 2003). Earlier studies concentrated on the translation of fiscal deficits into seigniorage, That is, as documented in Sargent and Wallace (1981), when a fiscally dominant country incurs fiscal deficit it finances itself thorough printing money. This, in turn, increases inflation. The impact of fiscal deficit on inflation is also well documented in the study of Montiel (1989). In his VAR study, Montiel showed that monetary

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<sup>38</sup> Jeannine Bailliu, Daniel Garcés, Mark Kruger, and Miguel Messmacher (2003), "Explaining and Forecasting Inflation in Emerging Markets: The Case of Mexico", Bank of Canada Working Paper 2003-17.

growth due to seigniorage was one of the main drivers of inflation in Argentina and Brazil. However, he also documented that his empirical findings favored balance of payments over the monetary growth as the main source inflation for Argentina, Brazil and Israel. Bruno and Fischer (1990) as well proposes that monetary policy cannot be replaced by fiscal policy because when monetary authorities compensate budget deficit through printing money under fiscal pressure, then fiscal authorities become the regulator of inflation rates. This may, in turn, result in higher than expected inflation rates. Rogers and Wang (1994) also suggest that higher deficits and higher inflation cause each other to spiral upward in their Mexican study. Furthermore, Catão and Terrones (2001), through their study over twenty three emerging markets, found that a one percentage point decline in the ratio of fiscal deficit to GDP, lower inflation by half to six percentage points depending on the size of inflation tax base. Another study by Fischer, Sahay, and Vegh (2002) found that there was a strong relation between inflation and fiscal deficit in countries with high-inflation.

However, as shown in Montiel (1989)'s study, the effect of fiscal deficit on inflation may also translate into a balance of payments crisis resulting in exchange rate depreciation that triggers inflation. According to Liviatan (1986) when a country runs persistent fiscal deficits, it will deplete its central bank's foreign reserves to finance its deficit. This, in turn, will cause a balance of payments crisis resulting in the depreciation of the national currency. Given the depreciation in currency then inflation will increase through increased inflationary expectations or the wage indexation mechanisms. Other views, govern the effect of external factors on a fiscal deficit running country that pursues passive monetary policies (Dornbusch, 1985). In sum, "the pass-through of a depreciation into domestic prices could be much larger than the share of imported goods in the consumption basket would suggest"<sup>39</sup>. Given this theoretical reasoning behind the relation between exchange rates and inflation, the study by Bailliu, Garcés, Kruger, and Messmacher (2003) found that the evolution of exchange rate in Mexico was an important factor for forecasting inflation.

Furthermore, the impact of exchange rate regimes is also an important factor for the level of inflation rates. In their VAR study, Loungani and Swagel (2001) found that the contribution of monetary growth is far less important in fixed exchange regimes than floating exchange regimes through their study for fifty three developing countries. They suggest that the

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<sup>39</sup> Jeannine Bailliu, Daniel Garcés, Mark Kruger, and Miguel Messmacher (2003), "Explaining and Forecasting Inflation in Emerging Markets: The Case of Mexico", Bank of Canada Working Paper 2003-17.

departure from fixed exchange regime can be inflationary. On the other hand, Broda (2006) found that developing nations with fixed exchange rate regimes have national price levels 20 percent higher than those with flexible regimes.

Other resources for inflation are related to the lack of independence of the central banks and inflation expectations. Studies measuring the relation between central bank independence and inflation asserted that inflation is lower among countries that have an independent central bank system. The reason is that an independent central bank can handle monetary policies more efficiently when there is no pressure of fiscal authorities. Bade and Parkin (1982), Alessina (1988, 1989), Grilli, Masciandro, and Tabellini (1991) found a negative relation between inflation and central bank independence. IMF (1996) showed that the inflation performance between 1970 and 1995 industrial countries was negatively correlated with an index of central bank independence. However, this relation did not hold for developing nations since there could be a divergence between de jure and de facto central bank independence. However, Loungani and Sheets (1997) found that there is negative correlation between central bank independence and inflation across the data from twenty five transition economies. Furthermore, Jacome (2001), through his study for Latin America countries during the period 1999-2001, found a negative relation between inflation and central bank independence.

On the other hand, inflation is, because of inertial forces (wage contracts, financial indexation, etc.), a serially correlated process<sup>40</sup>. Chopra (1985) confirmed the inflation inertia through a study over developing countries. He found that inflation is serially correlated because of the presence of inflationary expectations and staggered wage contracts. Furthermore, through a long memory model to test the persistence in inflation, Baum, Barkoulas, and Caglayan (1999) found significant evidence of long memory in inflation rates for both the industrial and the developing nations. Loungani and Swagel (2001) also found that inflation expectations played an important role in explaining the ten to twenty percent of inflation movements.

Though inflation may be a monetary phenomenon in the long run, the effects of supply shocks and demand-pull factors are important as well. However, in the emerging market case, Loungani and Swagel (2001) found that supply and demand factors were not significant over

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<sup>40</sup> Pierre-Richard Agénor and Mark P. Taylor (1983), "Analysing Credibility in High-Inflation Countries: A New Approach," *The Economic Journal*, Vol. 103, No. 417, pp. 329-336.

the prediction of inflation, besides the effects of inflation expectations, money, and exchange rates. Previous studies with Phillips Curve models on the effect of demand factors also confirm that demand pull factors were not highly significant in explaining inflation. “For example, the IMF (1996) found that the output gap explained little of the movement in inflation for developing countries. Inflation in these countries was better explained by changes in money growth and nominal exchange rates. This is not to say that inflation is not a function of excess demand in these countries. However, it appears that the contribution of excess demand is dominated by those of nominal shocks; in particular, inflation in the medium term is seen as the result of the government financing its deficit through the creation of money or through timeinconsistent monetary policy”<sup>41</sup>. As also shown in Coe and McDermott (1997), inflation over thirteen Asian countries was influenced by the output gap indicator. However, Phillips Curve models may not be very reliable due to their aforementioned gaps in the previous section.

Other than the monetary, Phillips Curve and time series models, markup models are also used for the analysis of inflation in emerging markets. These models relate domestic price levels to a mark-up over costs and wages, and to a measure of foreign prices expressed in domestic currency. Studies by Bailliu, Garcés, Kruger, and Messmacher (2003) for Mexico, Garcia and Restrepo (2001) for Chile, and Springer and Kfoury (2002) for Brazil showed that markup models performed well both in terms of in-sample and pseudo out-of-sample measures. Furthermore, Bailliu, Garcés, Kruger, and Messmacher (2003) found that their markup model outperformed both the Phillips Curve and monetary models through their study for explaining and forecasting inflation in Mexico. However, as Bailliu, Garcés, Kruger, and Messmacher (2003) suggests the adoption of inflation targeting and flexible exchange rates regimes (especially in Brazil and Chile) caused these models to underperform by having parameter instability. Therefore, these models should be used with caution and be compared to other alternatives to ensure their predictive ability.

The studies on Turkish inflation have also been in line with those of the international cases<sup>42</sup>. Examples of the studies investigating the inflation behavior prior to 1980 are Akyuz (1973), Ertugrul (1982), Aksoy (1982) and Togan (1987). Through his combined adaptive

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<sup>41</sup> Jeannine Bailliu, Daniel Garcés, Mark Kruger, and Miguel Messmacher (2003), “Explaining and Forecasting Inflation in Emerging Markets: The Case of Mexico”, Bank of Canada Working Paper 2003-17.

<sup>42</sup> This part largely draws on Kibritcioglu (2002).

expectations demand for money model, Akyuz (1982) found that inflation could be explained by the changes in the money supply, real income, and the non-monetization ratio during the period 1950-1968. On the other hand, Ertugrul (1982)'s simultaneous-system equations based on deseasonalized quarterly data for the period 1970-1978 showed that inflationary expectations were the major factor for inflation in Turkey. Furthermore, Aksoy (1982)'s study for testing monetarist and structuralist models on Turkish data through the period from 1950 to 1979 found that money and inflation were not proportionally related, but their relation depended both on the inflationary expectations and the nature of foreign exchange availability. In addition, Aksoy also found little evidence on the cost push effects that operates through money supply mechanism rather than cost push pressures. Finally, Togan (1987) found that inflation for the period 1960-1983 was determined by the time path of money and interest rates.

Studies investigating the Turkish inflation behavior after 1980 are much larger. This may be attested to the changing nature of the economy through an open market system and accelerating inflation rates during the period.

Öniş and Özcumhur (1990) was perceived as the main reference point for many authors of the time. With their four variable VAR and three stage simultaneous equation models, Öniş and Özcumhur (1990) found, through the analysis of the monthly data from 1981 to 1987, that supply side factors had significant effect on Turkish inflation and devaluations at the time were inflationary. Furthermore, they concluded that the inflation may not be investigative with a pure monetarist approach. However, Rittenberg (1993) argued that, according the Granger Causality tests, the causality direction was from inflation to exchange rate changes but not from exchange rate changes to inflation.

On the other hand Özatay (1992) found, based on his econometric estimation of sectoral price equations, Granger causality tests, and simulations for the period 1982-1990 that there was a considerable amount of inertia in the private sector prices due to cost factors coming from energy, lending rate, agricultural and import prices. However, wages were negligible source of cost for inflation.

Yeldan (1993) through his general equilibrium analysis with Keynesian features focused on the structural and distributional aspects in Turkish inflation. He found that public sector

expenditures created demand pull inflation in Turkey and that the asymmetric distribution of wealth among socio-economic classes played an important role on the price movements in Turkey. Further, he showed that there was a strong cost-push effect arising from the profit/rent inflation fed by increases in monopolistic producer mark-ups over prime costs and from the devaluation of exchange rates in Turkey in 1980s.

Further causes of cost push factors were also analyzed under the once-and-for-all impacts of oil prices on Turkish inflation. With their iterations based on Turkish input-output tables from 1979, 1985 and 1990, and five variable VAR study, Kibritçioğlu and Kibritçioğlu (1999) found that a hypothetical twenty percentage point increase in crude oil prices causes a cumulative increase in the general price increase by around 1.1 percentage point within ten months. Furthermore, VAR results showed that nominal exchange rates and past values of inflation were the main determinants of inflation for the period 1986-1989. Kibritçioğlu (2002) argued that the negligible effect of oil prices on Turkish inflation may have been attested to the lack of dynamic mechanism which could have generated continuous increases in the price level. In addition, the decreasing dependence on oil as energy resource after 1980s could have also lessened the impact of oil prices in inflation.

The impact of public sector expenditures on Turkish inflation is also found by Metin (1995). He found that the fiscal expansion was a determining factor of inflation during the period from 1950 to 1988. That is the excess demand for money due to fiscal deficit affects inflation positively in the short run. Therefore in order to reduce inflation the government should have reduced the budget deficit. On the other hand, some studies suggested the necessity to design an exchange rate based stabilization program to reduce inflation since depreciation has a strong impact on inflation. [İnsel, 1995; Erol and van Wijnberg, 1997; Lim and Papi, 1997; Agénor and Hoffmaister, 1997; Darrat, 1997; Akyürek, 1999]

Other effects arising from the exchange rates may be attributed to currency substitution in Turkey. After domestic citizens were allowed to open foreign exchange deposit accounts in Turkish banks in 1984, there has been an increasing currency substitution. This could be attested to the inflationary expectations in the market at the time. That is, domestic citizens free from national currency to avoid future inflation tax. In this case both demand and exchange rates become unstable. The effects of currency substitution on unstable exchange rates and seigniorage maximizing rate of inflation in Turkey were investigated by Selçuk

(1994, 1997 and 2001), Scacciavillani (1995) and Akçay, Alper and Karasulu (1997). These studies mainly reported that exchange rate substitution created instability in exchange rates [Scacciavillani, 1995], and further, due to currency substitution the government could not collect more seigniorage revenue to finance budget deficits and set the growth rate of monetary base at a higher level for financing purposes [Selcuk, 2001].

In recent papers the increasing role of inertia in the process of Turkish inflation has taken considerable place. Akçay, Alper and Özmucur (1997), Lim and Papi (1997), Agénor and Hoffmaister (1997), Alper and Üçer (1998), Akyürek (1999), Cizre-Sakallioğlu and Yeldan (1999), and Baum et al. (1999) found the particular role of the inertia in Turkish inflation. Akçay, Alper and Özmucur (1997) found, based on their VAR and VEC study for the annual data from 1948 to 1994 and quarterly data from 1987 to 1995, that the inertia in inflation was increasing due to the accumulation of inflationary expectations in the period 1987-1995. budget deficit had significant role in inflation Lim and Papi (1997) also found the quantitative importance of inertia through OLS estimations and cointegration tests on a multi-sector econometric with short and long run dynamics from the quarterly data from 1970 to 1995. Further VAR studies by Agénor and Hoffmaister (1997), Alper and Üçer (1998), Akyurek (1999) reached to similar conclusions. In addition, with their Political Economy approach and Hodrick-Prescott Filtering method for the quarterly data from 1987 to 1996, Cizre-Sakallioğlu and Yeldan (1999) found that much of the price dynamics in Turkey was governed by inertial factors rather than shifts in the monetary variables such as money supply and the fiscal deficit. Baum et al. (1999), with semi-parametric and maximum likelihood estimation methods, found also that long memory in the CPI-based inflation rate was a general phenomenon for Turkey. In support of this view, Erlat (2001) showed with unit root tests and ARFIMA models for the monthly data from 1987 to 2000 that the monthly inflation rate was essentially stationary but had generally significant long memory component. Finally, Diboglu and Kibritçioğlu (2001) showed based on their dynamic open market aggregate supply-aggregate demand model with imperfect capital mobility and SVARs for the quarterly data from 1980 to 2000 that core inflation was a major component of Turkish inflation. However, a recent article by Celasun, Gelos and Prati (2003) found with their univariate analysis and modified Calvo (1983) model for the period between 1994 and 2002 that the degree of inflation persistence in Turkey was much lower than in Brazil and Uruguay prior to their successful stabilization programs. Further, they showed that the inflation process was

forward looking rather than backward looking in Turkey. Using survey data, they also found that inflation expectations, in turn, depended largely on the evolution of fiscal variables.

Further implications of the above studies also show that budget deficit and mainly exchange depreciation has substantial role in inflationary process in Turkey [Akçay, Alper and Özmucur, 1997; Lim and Papi, 1997; Agénor and Hoffmaister, 1997; Akyurek, 1999]. However, Alper and Üçer (1998) indicated that budget deficit and inflation relation was weaker than one might have thought. But, as shown by Akçay, Alper and Özmucur (1997), this could be due to bond financing after 1986. Further studies on the impact of exchange rates on Turkish inflation has been conducted under the “*exchange-rate-pass-through*” literature that concentrates on measuring the transmission degree of a change in nominal exchange rates to domestic wholesale and/or consumer price indices. Using a recursive VAR model for Turkey, for example, Leigh and Rossi (2002) founded that (i) the impact of the exchange rate on prices is over after about a year, but is mostly felt in the first four months, (ii) the pass-through to wholesale prices is more pronounced compared to the pass-through to consumer prices, and (iii) the estimated pass-through is complete in a shorter time and is larger than estimated for other key emerging market economies. Furthermore, Selçuk (2004) reports that the exchange-rate-pass-through in Turkey is around 35 to 50 percent. Consequently, a slowdown in nominal exchange-rate depreciation would result in a smaller inflation. Similarly, nominal appreciation would have some deflationary effect on prices”<sup>43</sup>.

## **5- Estimation and Forecast Study**

For estimating and forecasting inflation, I used Maliszweksi (2003)’s equation and compared its performance to an AR(2) model and a STAR model. Wojciech Maliszewski developed this model to estimate the inflation at Georgia. This theory suggests that, in equilibrium, and over the long run, prices increase with increasing money supply and depreciating currency, and decrease with growth (increasing GDP). As a result, Maliszweksi formulated the theory in the following way:

$$p = \alpha_1/(\alpha_1 + \alpha_2)m + \alpha_1/(\alpha_1 + \alpha_2)e - 1/(\alpha_1 + \alpha_2)y$$

Where;  $p = CPI$ ;  $m = M2Ycb$ ;  $e = XRE$ ; and  $y = GDP$ . Please note that all the variables are in logarithmic form.

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<sup>43</sup> Aykut Kibritçioğlu (2004), “A Short Review of the Long History of Turkish High Inflation”, Department of Economics, Faculty of Political Sciences, Ankara University.

This equation is also well in line with the aforementioned impacts of variables to inflation in emerging market economics. Therefore, the use of Maliszewski (2003)'s equation is intended to fill the gap that did not use these variables under a structural model for predicting Turkish inflation.

#### 5.1- Maliszewski's Equation for inflation forecast<sup>44</sup>.

Long-term price level (P) behavior is assumed to be governed by the balance between aggregate demand (YD) and supply (YS) of goods and services. The aggregate demand for goods and services is a function of real money supply (M/P) and the real exchange rate (E/P). In log-linear form (denoted by lower-case letters), the aggregate demand is written as:

$$y_D = \alpha_1 (m - p) + \alpha_2 (e - p) \quad (1)$$

The aggregate supply is exogenously given and in equilibrium is equal to aggregate demand and real income (Y):

$$y = y_S = y_D \quad (2)$$

It is assumed that the goods market is always in equilibrium and therefore equation (2) always holds.

Flow demand for foreign exchange (current account deficit) is assumed to be a function of real exchange rate and real income. Real income is fixed at the level of aggregate supply, the available foreign financing is exogenously given, and the real exchange rate tends to equilibrate the foreign currency market. Money demand is assumed to be a function of real income. Similarly, since real income—the only variable entering the real money demand function—is exogenous, real money balances tend to equilibrate the money market. If the foreign exchange and the money market are in equilibrium, the goods market described by equation (1) is also in equilibrium by application of the Walras law.

If the markets are in equilibrium, the simple model determines two real variables (m-p and e-p), leaving one degree of freedom for determination of nominal variables (m, e and p). Fixing one of the nominal variables determines the other two, providing a nominal anchor for the

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<sup>44</sup> This part is taken from Wojciech Maliszewski (2003), "Modeling Inflation in Georgia", IMF Working Paper, European II Department, WP/03/212.

system. Empirically, if the markets are on average in equilibrium, it is likely that two unique long-run cointegrating vectors emerge between non-stationary nominal variables in equation (1) (treating  $y$  as exogenous). The two cointegrating vectors describe equilibrium in any two of the three markets and equilibrium in the omitted market is described by a linear combination of the two unique cointegrating vectors, again by application of the Walras law.

It is also possible that the money and foreign exchange markets are persistently out of equilibrium (adjustments towards equilibrium may be very slow or non-linear) and that only the goods market is—by assumption—always in equilibrium. In this situation, fixing one of the nominal variables no longer provides nominal anchor for the system, but fixing any two still determines a third one by equation (1). Empirically, if the two markets are out of equilibrium, only one cointegrating vector can be found in the data, corresponding to the equilibrium described by equation (1). The persistent pressure on exchange rate before the Russian crisis—discussed in Section I above—may be an example of a disequilibrium of this type in one of the markets. The disequilibrium in the foreign exchange market in this period would imply that the money market was also out of equilibrium. The shift in real money holdings during the crisis gives some support to this hypothesis. While equilibrium in the foreign exchange and money markets had been ultimately restored, the persistence of disequilibrium and a possibly non-linear adjustment process may preclude finding two cointegrating vectors among the series. Assuming that only goods market is in equilibrium, substituting (2) into (1) and solving for  $p$  gives the equilibrium price level:

$$p = \alpha_1/(\alpha_1 + \alpha_2)m + \alpha_1/(\alpha_1 + \alpha_2)e - 1/(\alpha_1 + \alpha_2)y \quad (3)$$

Equation (3), similar to the price equation developed by Bruno (1993), describes a long-term relationship between prices, exchange rate, money and real income, suitable for estimation and testing in the cointegration framework even if money and foreign exchange markets are persistently out of equilibrium. The equation exhibits a neo-classical dichotomy:  $yS$  is fixed and equi-proportional changes in nominal variables leave the two real variables ( $m-p$  and  $e-p$ ) unaltered. Testing for the neo-classical dichotomy is equivalent to testing that the coefficients of money and exchange rate sum up to one.

## 5.2-Data

The data used are the past historical quarterly data between 1988Q1 and 2005Q4. The variables used are consumer pricing index (CPI), exchange rates (XRE), money supply (M)

and gross domestic production (GDP). Given the economics theory, in the equation used for estimation CPI is set as the dependent variable over the explanatory variables GDP, XRE and M. In more detailed expression, the data description and the resource is given in the table here below:

*XRE* : End of period Exchange Rate ( Liras per Dollar, buying rates) ( taken from the Central Bank of Turkey)

*M2Ycb*: Money in billion TL (data is taken from the Central Bank of Turkey)

*CPI*: Consumer price index (1995=100) (taken from International Financial Statistics CD and Turkish Statistical Institute)

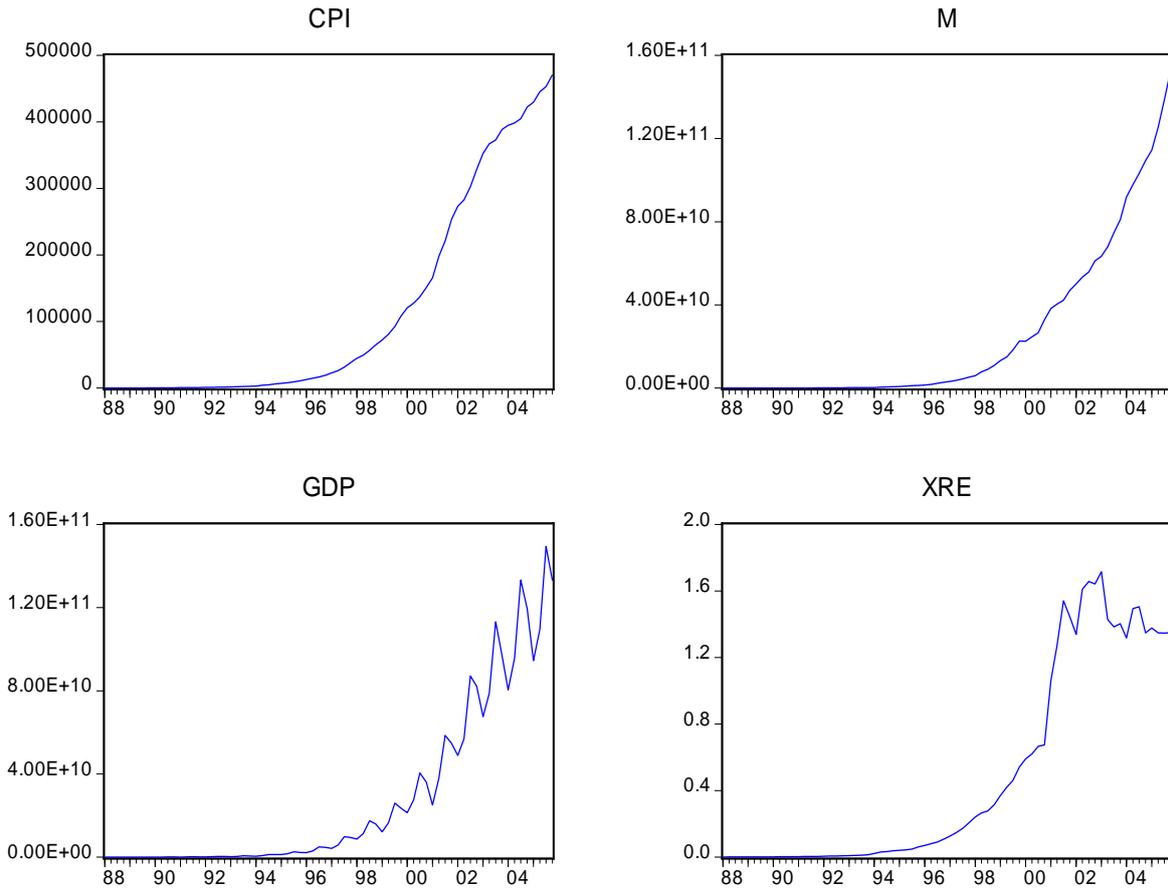
*GDP*: Real GDP (1995=100) (taken from International Financial Statistics CD and Turkish Statistical Institute)

Once the above data is obtained then it is fed into EViews 5.0 statistical package program and seasonally adjusted according to some version of Census X11 procedure.

### *5.3- Estimation Methodology and Results*

#### *5.3.1- Maliszweksi's equation*

From the graphs of the actual values below, the non-stationary (increasing) pattern of inflation, money supply, exchange rate and gross domestic product in Turkey can be easily seen. This suggests that a regular OLS estimation would result in a spurious relation. Thus, in order to conduct a correct estimation procedure the randomness arising from stochastic and deterministic trends should be removed and the values should be reduced to stationary processes.



**Graph 1: Variables**

After seasonally adjusting the data, I take the logarithm of the variables. Then, I tried to make them stationary through differencing method under the application of ADF test given a user specified lag length criteria. The variables are tested with critical values at 5.00%. The summary of results here below indicates that the logarithm of all data series ( $E$ ,  $M$ , and  $P$  and  $Y$ ) are **I(1)** since the pertaining probability values for the ADF test statistic results are below the critical value of 5.00%. Further details in regards to the results of ADF tests may be found in appendix A.

However, in the literature, there is general discussion whether the time series path of macro variables are  $I(1)$  or  $I(2)$ <sup>45</sup>. For the Turkish case, given the aforementioned methodology, these variables are found to be  $I(1)$ . A different approach could have found an  $I(2)$  process in the time series path of these variables due to structural breaks in Turkish economy. To consider this point, I compare the findings of Maliszweksi's equation with a non-linear model that captures the asymmetric behavior in the time series path of inflation. More detailed analysis is carried in further sections.

<sup>45</sup> See Nelson and Plosser (1982) and Rudenbusch (1992).

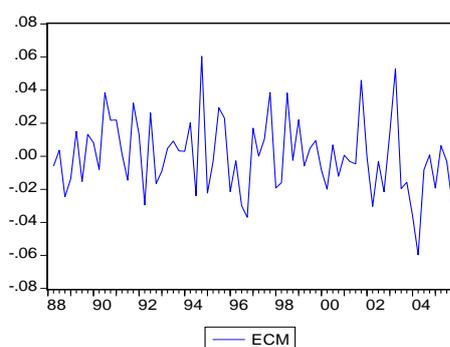
ADF test statistic results for explanatory variables				
Integration Level	Ln(E)	Ln(M)	Ln(Y)	Ln(P)
I (1)	-3.398868 (0.0144)	-4.241105 (0.0012)	-3.455207 (0.0123)	-3.867474 (0.0037)

Values between parentheses are probability values.

Furthermore, the table below gives the summary of results for the number of lags for each variable (further details may be found in appendix A). These results suggest that the first differences of the variables are in relation with their first lags and that the intercepts for all variables are significantly different than zero.

Dependent Variable	Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\Delta Ln(P_t)$	D(LCPISA(-1))	-0.382060	0.098788	-3.867474	0.0002
$\Delta Ln(P_t)$	C	0.042453	0.012492	3.398270	0.0011
$\Delta Ln(E_t)$	D(LEXSA(-1))	-0.535120	0.157441	-3.398868	0.0012
$\Delta Ln(E_t)$	D(LEXSA(-1),2)	-0.068949	0.162185	-0.425129	0.6722
$\Delta Ln(E_t)$	D(LEXSA(-2),2)	0.060846	0.149052	0.408219	0.6845
$\Delta Ln(E_t)$	D(LEXSA(-3),2)	0.193836	0.125618	1.543057	0.1279
$\Delta Ln(E_t)$	C	0.052233	0.019480	2.681388	0.0094
$\Delta Ln(M_t)$	D(LMSA(-1))	-0.669764	0.157922	-4.241105	0.0001
$\Delta Ln(M_t)$	D(LMSA(-1),2)	-0.215214	0.119746	-1.797247	0.0769
$\Delta Ln(M_t)$	C	0.086173	0.022283	3.867172	0.0003
$\Delta Ln(Y_t)$	D(LYSA(-1))	-0.521893	0.151045	-3.455207	0.0010
$\Delta Ln(Y_t)$	D(LYSA(-1),2)	-0.330107	0.118835	-2.777873	0.0071
$\Delta Ln(Y_t)$	C	0.061627	0.019883	3.099478	0.0028

Since  $E$ ,  $M$ , and  $P$  and  $Y$  are all **I(1)** then we can look for a long-run relationship between them by testing for cointegration. This involves taking the regression of the logarithm of  $P$  on the logarithms of  $E$ ,  $M$  and  $Y$ , and testing the residual's integration level with ADF. If the residuals are  $I(0)$ , then we say that the variables are cointegrated. The graph 2 below shows the path of the residuals obtained from the regression described above.



Graph 2: Plot of Errors

The graph on the next suggests that the residuals follow a stationary path. The test statistic results below also suggest that the residuals are  $I(0)$ , since the probability value indicates the stationary behavior of residuals. From this we reject the null hypothesis of non-stationarity and conclude that the price level is cointegrated with exchange rates, output, and money.

Null Hypothesis: ECM has a unit root

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-6.374320	0.0000
Test critical values:		
1% level	-2.599934	
5% level	-1.945745	
10% level	-1.613633	

For further details on the test statistic above please refer to appendix B.

Once the cointegration property among  $\Delta Ln(P_t)$ ,  $\Delta Ln(E_t)$ ,  $\Delta Ln(M_t)$ , and  $\Delta Ln(Y_t)$  is shown then it remains to comment on the long run property among the variables. The results here below show the long run impacts of  $\Delta Ln(E_t)$ ,  $\Delta Ln(M_t)$ , and  $\Delta Ln(Y_t)$  on  $\Delta Ln(P_t)$ . (Please refer to appendix B for further details.)

<i>Dependent Variable: <math>\Delta Ln(P_t)</math></i>	
<b>Variable</b>	<b>Coefficient</b>
intercept	0.011847
$\Delta Ln(E_t)$	0.228002
$\Delta Ln(M_t)$	0.166749
$\Delta Ln(Y_t)$	0.482126

The results above show that the price level is positively related to the growth in exchange rate, money and output. This conclusion is well in line with the theoretical suggestion, as the growth in money and output and depreciation causes an increase in inflation in the long run. Thus, one percentage point increase in exchange rate, money and output increases inflation by an amount equivalent to the value of coefficients. That is, in the long run, a one percentage point increase in exchange rate, money and output increases inflation respectively by around 0.23, 0.17 and 0.48 percentage points.

After I ensured the cointegration property, I then proceed to build the error correcting model. This involves running a regression for the model here below:

$$\Delta P_t = \alpha_0 + \sum_{i=1}^n \beta_i \Delta P_{t-i} + \sum_{i=0}^n \gamma_i \Delta E_{t-i} + \sum_{i=0}^n \lambda_i \Delta M_{t-i} + \sum_{i=0}^n \theta_i \Delta Y_{t-i} + \delta ECM_{t-1} + \varepsilon_t$$

$$\text{Where, } ECM_{t-1} = P_{t-1} - (\alpha_0 + \beta_1 M_{t-1} + \beta_2 E_{t-1} + \beta_1 Y_{t-1})$$

This equation ensures the short run effects of the growth in money, exchange rate and output to the inflation. The parsimonious ECM model results are here below. Further details are supplied in appendix C.

**Dependent Variable:  $\Delta \ln(P_t)$**

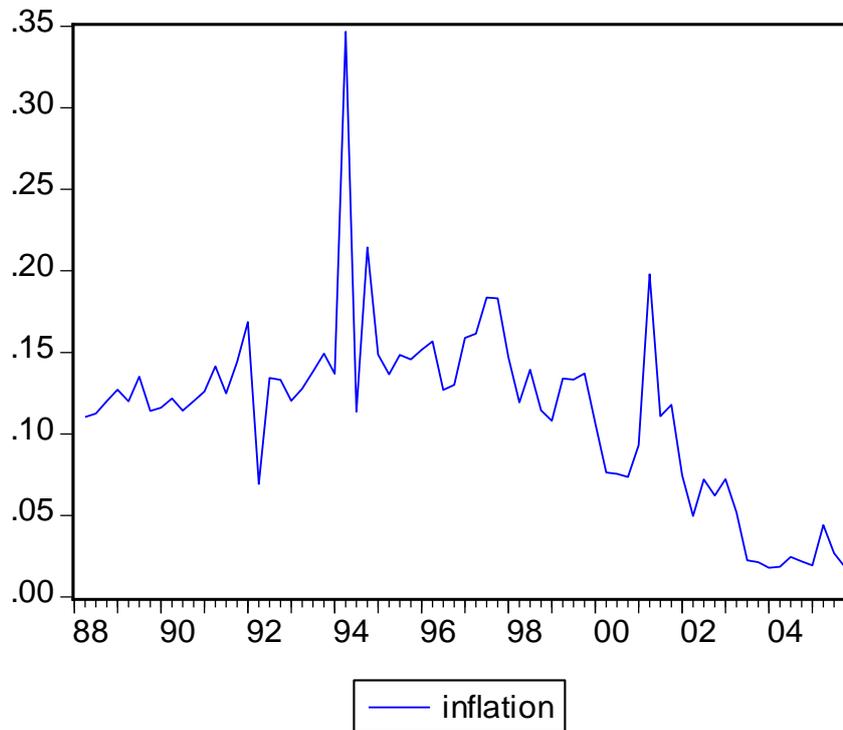
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>t-Statistic</b>	<b>Prob.</b>
<i>intercept</i>	-0.003570	0.006737	-0.529873	0.5982
$\Delta \ln(P_{t-1})$	0.512102	0.150116	3.411367	0.0012
$\Delta \ln(E_t)$	0.190431	0.026786	7.109430	0.0000
$\Delta \ln(M_t)$	0.136917	0.034366	3.984079	0.0002
$\Delta \ln(M_{t-1})$	-0.163175	0.046907	-3.478685	0.0010
$\Delta \ln(M_{t-2})$	0.087252	0.035914	2.429426	0.0182
$\Delta \ln(Y_t)$	0.293868	0.051233	5.735896	0.0000
$\Delta \ln(Y_{t-1})$	-0.210756	0.075688	-2.784519	0.0072
$\Delta \ln(Y_{t-2})$	0.182205	0.036645	4.972104	0.0000
$ECM_{t-1}$	-0.400817	0.159229	-2.517235	0.0146

*Adjusted R-squared: 0.892267*

From t-statistic and probability values we may see that inflation is positively affected by the contemporaneous depreciation and monetary and output growths ( $\Delta \ln(E_t)$ ,  $\Delta \ln(M_t)$ , and  $\Delta \ln(Y_t)$ ). This significant relation can be understood from the positive coefficients of the variables and from the t-statistic and p-values. Therefore, a percentage point increase in these variables, increase inflation in the short run by around 0.19, 0.14, and 0.29 percentage points respectively. This finding suggests that the path of inflation in Turkey is more affected by the structural factors than monetary and international factors since the coefficient of the contemporaneous output growth is the largest. Furthermore, the impact of the depreciation is higher than the impact of monetary growth suggesting the exposure of Turkish economy to international effects. Also, the positive coefficients of the contemporaneous depreciation and monetary and output growths suggest the expansionary policy followed by Turkey throughout the years given the fact that Turkey is an emerging market.

On the other hand, the presence of the lags show the significance of adjustment lags in Turkish economy. The fact that both monetary and output growths have lags shows that Turkish inflation is prone to the impacts of earlier policies. The impact of the first lags of monetary growth and output growth variables tend to affect inflation negatively. But, the second lags of these variables are in positive relation with inflation. This might be explained with the historical path of the inflation in Turkish economy. Turkey has experienced high inflation for the last twenty years or so. However, though inflation was high, as we can see in the graph below, it has been capped given the historical fact that the government tended to follow policies to decrease the inflation when it was higher during the previous periods. Therefore, if early policies (as can it can be understood from the positive coefficients of the second lags of money monetary growth and output growth) cause inflation to be higher, later

policies (the negative coefficients of the first lags of monetary growth and output growth) tend to decrease inflation. That is, while a percentage point increase in the first lag of monetary and output growths decreases inflation by around 0.16 and 0.21 percentage points respectively, a percentage point increase in the second lags of monetary and output growths increases inflation by around 0.09 and 0.18 percentage points.

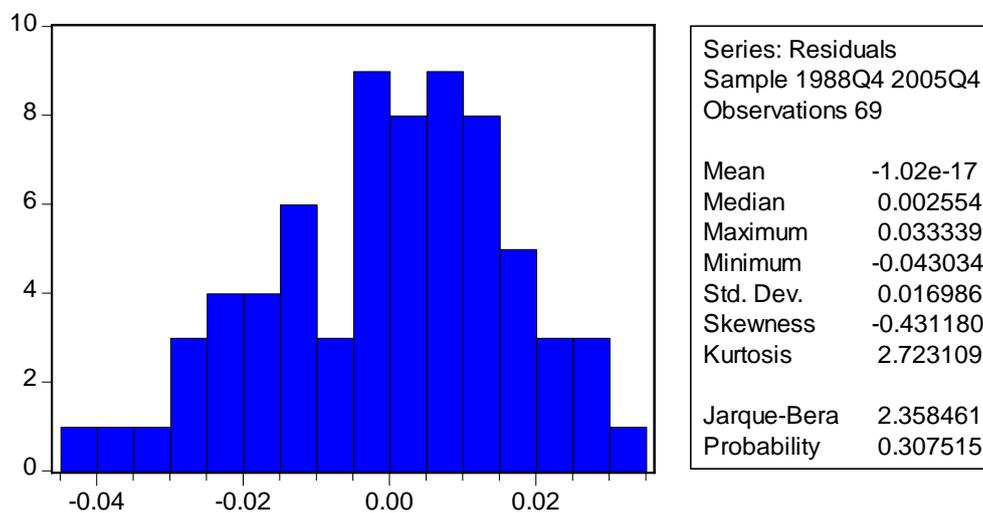


**Graph 3: Quarterly Path of Turkish Inflation**

On the other hand, the significant coefficient of the lagged inflation shows the impact of previous inflation values on current values. Since its coefficient has the largest value, we may deduce that inflation inertia in Turkey due to inflationary expectations played a significant role in the time series path of Turkish inflation. Therefore, a percentage point increase in  $\Delta P_{t-1}$  increases inflation by around 0.51 percentage points. In addition, the negative coefficient of the error correcting model shows impact of the long run adjustments to Turkish inflation. Thus, when inflation deviates from its long run path, it adjusts to its fair value with a speed equivalent to the coefficient value of ECM. That is, if inflation is higher than the long run rate that the model suggests, then the negative coefficient of ECM pulls inflation back to its expected long run value by an amount equivalent to the multiplication of ECM's coefficient and the divergence.

Given the above findings, I also ran several diagnostic tests in order to ensure the reliability of the statistical results above. The summary of the results can be seen in the table here below. Further details are provided in appendix D.

<b>Statistical Test Results</b>				
<b>Test</b>	<b>Statistic Value</b>	<b>P-value</b>	<b>Null Hypothesis (H<sub>0</sub>)</b>	<b>Reject / Not Reject H<sub>0</sub></b>
Jarque-Bera	2.358461	0.307515	Normality	Not Reject
LM Test	0.155388	0.856445	No serial correlation	Not Reject
White Heteroskedasticity Test	0.695582	0.798863	Homoscedastic	Not Reject
Chow Breakpoint Test (1996 Q1)	2.694979	0.010275	No Structural Change	Reject
Chow Breakpoint Test (2001 Q3)	2.127756	0.039720	No Structural Change	Reject
RESET Test	3.655705	0.060821	Correct Specification	Not Reject
ARCH Test	0.988629	0.377528	No ARCH Effect	Not Reject



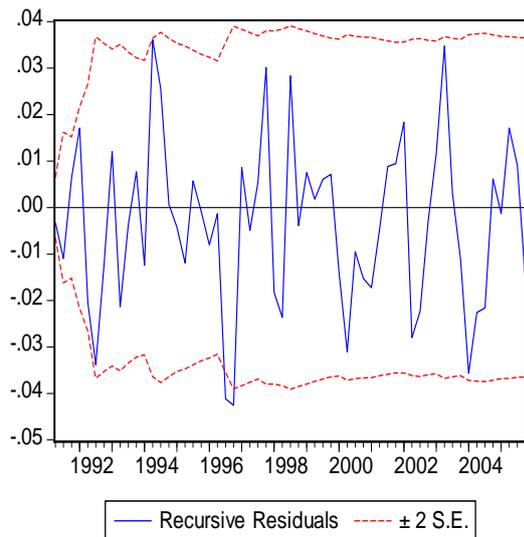
**Graph 4: Histogram for Normality Test**

The first diagnostic test, Jarque-Bera test shows us that we do not reject the null hypothesis of normally distributed residuals. This can also be seen from the plot and the statistical results of the histogram above. The fact that the residuals are normally distributed makes our testing procedure reliable.

The LM test indicates no serial autocorrelation in the residuals. Therefore, our equation is not subject to autocorrelation. Moreover, after running White Heteroskedasticity Test we also see that disturbances have constant variance. Thus, the model is not subject to heteroscedasticity as well. This can also be confirmed from the results of ARCH test.

For the Chow Breakpoint Test I used 1996 Q1 and 2001 Q3 as the breakpoints, because a huge financial crisis that happened in previous periods might have caused a structural change

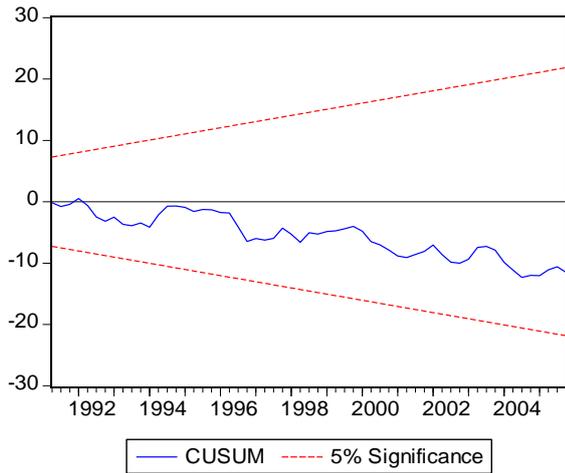
in the model. According to the above results I found out that there has been a structural break in the time series path of Turkish inflation. Furthermore, RESET test confirms that the model is correctly specified making us somewhat happy about the reliability of specification of our variables. However, this result should be interpreted with caution since the pertaining p-value is slightly different that the critical level of 5.00%. Thus, in order to make the findings of the model more reliable, I ran further stability tests.



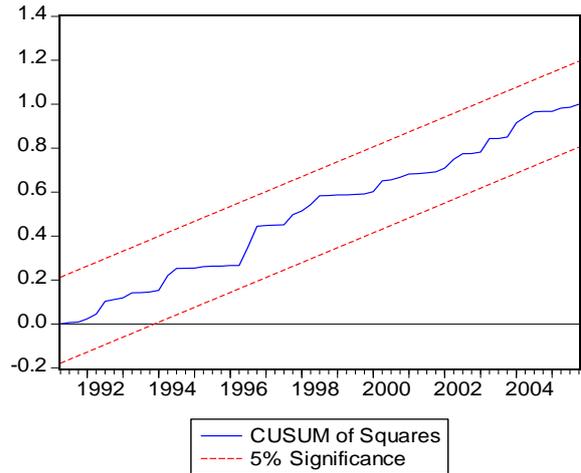
**Graph 5: Plot of Recursive Residuals**

The graph on the next shows a plot of the recursive residuals about the zero line. Plus and minus two standard errors are also shown as the dotted lines at each point. Residuals outside the standard error bands suggest instability in the parameters of the equation. Therefore, around 1994, 1996, 2002 and 2004 parameters of the equation seem to become slightly (1996 is the heaviest) unstable due to financial problems of the time. This instability seems to be also in line with the structural break points identified with the chow breakpoint tests above.

The graphs below plot the cumulative sum together with the 5% critical lines. Here we try to find parameter instability if the cumulative sum goes outside the area between the two critical lines. According to the graphs we can say that our parameters are stable since the line stays in between the 5% critical lines. Therefore, we might be able to obtain good forecast results by using the current regression model.

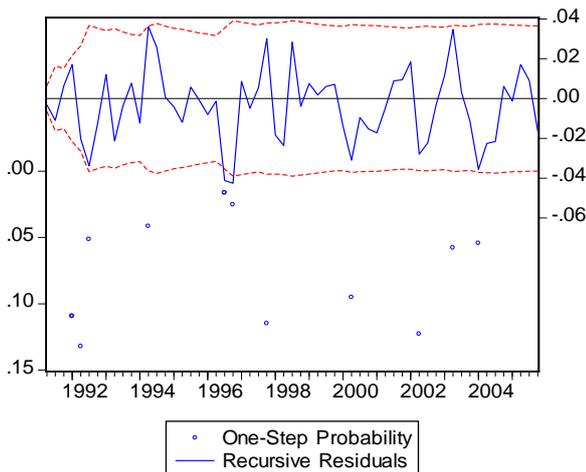


**Graph 6: Cumulative Sum**

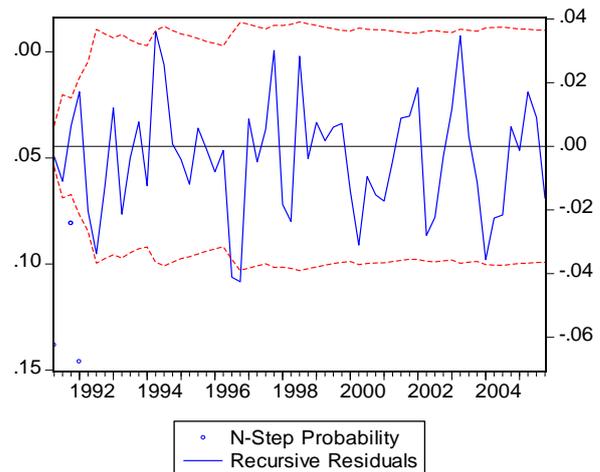


**Graph 7: Cumulative Sum of Squares**

Graph 8 is The One-Step Forecast Test which produces a plot of the recursive residuals and standard errors and the sample points whose probability value is at or below 15 percent. From this plot we spot the least successful periods around years 1994, 1996, 2002 and 2004 since the points with p-values less the 0.05 correspond to those points where the recursive residuals go outside or approximate to the two standard error bounds. In graph 9, N-step probability test computes all feasible cases, starting with the smallest possible sample size for estimating the forecasting equation and then adding one observation at a time. The points outside the band again show the least successful periods.



**Graph 8: One Step Probability**



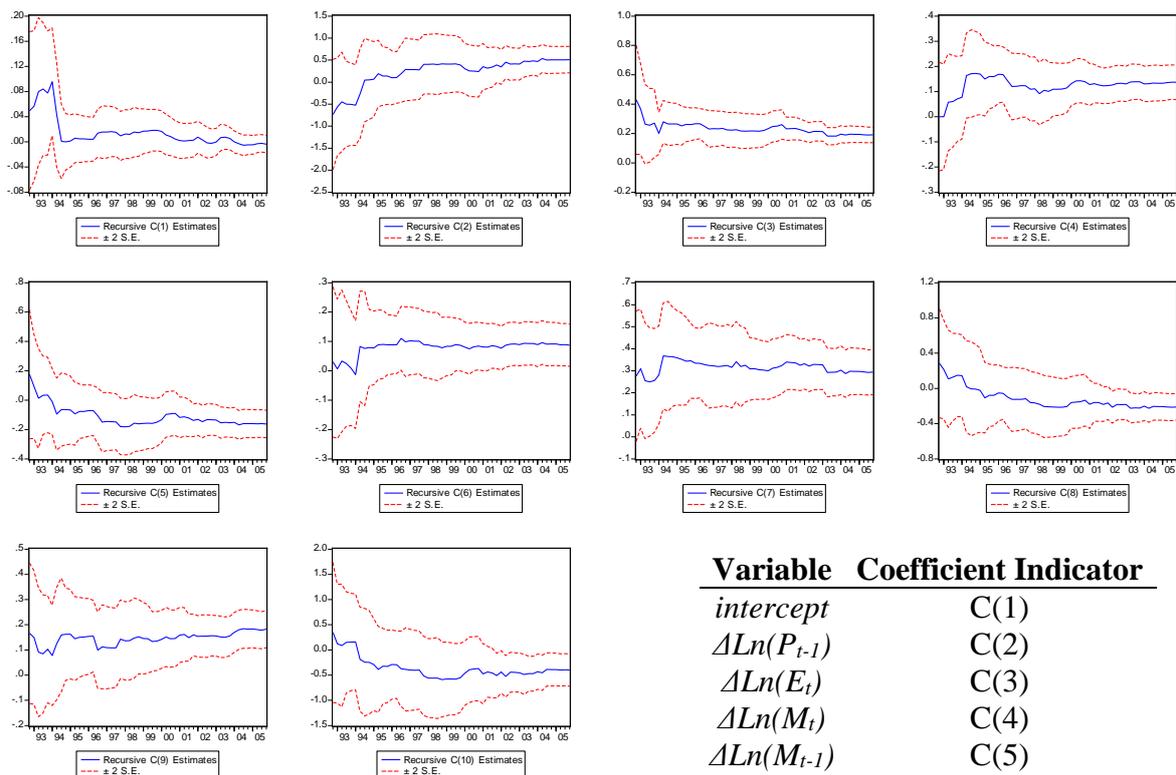
**Graph 9: N-Step Probability**

Finally, according to the recursive coefficient graphs below almost all variables have significant variances in the short run. Generally, the recursive coefficient graphs of the variables in the model make sudden movements and stabilize at new level. However, in the

medium and the long run the variables seem to stabilize as more data over the sample period are added. The coefficients of  $\Delta E_t$ ,  $\Delta M_t$ , and  $\Delta Y_t$  seem to follow a more stable path when the model uses more data. On the other hand, the coefficients of the first lag variables and ECM become negative given the application of the same procedure. Further, the coefficients of the second lags seem to follow a more stable path than those of the first lag variables. The only apparent instability is seen with the intercept, however it is not significantly different than zero as it can be seen that its coefficient value stabilizes around zero as more data are used. In addition, the coefficient of the first lag of inflation becomes positive as more data is used.

Although we may see the further variations in the recursive coefficients graphs, they usually appear only one time and they are relatively small. Thus, depending on the previous tests and on the fact that the coefficients become somewhat stable as more data is utilized, we may say that our model can be used to forecast inflation in a reliable fashion.

**Graph 10: Recursive Coefficients**



Variable	Coefficient Indicator
<i>intercept</i>	C(1)
$\Delta \text{Ln}(P_{t-1})$	C(2)
$\Delta \text{Ln}(E_t)$	C(3)
$\Delta \text{Ln}(M_t)$	C(4)
$\Delta \text{Ln}(M_{t-1})$	C(5)
$\Delta \text{Ln}(M_{t-2})$	C(6)
$\Delta \text{Ln}(Y_t)$	C(7)
$\Delta \text{Ln}(Y_{t-1})$	C(8)
$\Delta \text{Ln}(Y_{t-2})$	C(9)
$ECM_{t-1}$	C(10)

### 5.3.2- AR(2) Model

An ARMA process has the following general form:

$$r_t = \phi_0 + \sum_{i=1}^p \phi_i r_{t-i} + a_t - \sum_{i=1}^q \theta_i a_{t-i}$$

Where  $\sum_{i=1}^p \phi_i r_{t-i}$  drive the AR process and  $\sum_{i=1}^q \theta_i a_{t-i}$  drives the MA process.

ARMA(p,q) process is used as a benchmark model for the evaluation of the forecast performance of alternative models. I followed the regular procedure for obtaining the AR(2) process. That is, after running the regression of inflation on an intercept, I checked the “correlogram” of the residuals. The values of autocorrelation (AC) and partial autocorrelation (PAC) in the correlogram along with their Q-statics and Box-Jenkins p-values indicate whether inflation is an ARMA(p,q) or an AR(p) or a MA(q) process. Once the model is built then, I checked the correlogram again whether the residuals are white-noise. Basically, building an ARMA(p,q) process involves in measuring the impact of lags and shock to current values by making the residuals white-noise. The correlogram results indicated that inflation is an AR(2) process. After running an AR(2) model I checked the correlogram (please refer to appendix E) again. The results indicate that the residuals are white noise since any further lags of AC or PAC are not significantly different than zero.

The table below gives the result of the regression for AR(2) process (please see appendix F for further details). From the t-statistic and probability values we may see that the intercept and the coefficients of the lags are both significant at %5 critical level. However, the intercept is insignificant as its probability value is much larger than the 5.00% critical probability value.

Furthermore, the general conclusion from these findings suggest that quarterly inflation measures for the period 1988-2005 in Turkey are correlated to inflation measures from previous quarters. This might be the indication of the inflation inertia arising from the inflationary expectations in Turkish markets.

<i>Dependent Variable: <math>\Delta \ln(P_t)</math></i>				
<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>t-Statistic</b>	<b>Prob.</b>
C	0.016803	0.012271	1.369384	0.1755
DCPI(-1)	0.321797	0.107246	3.000556	0.0038
DCPI(-2)	0.514262	0.109385	4.701397	0.0000

*Adjusted R-squared: 0.510092*

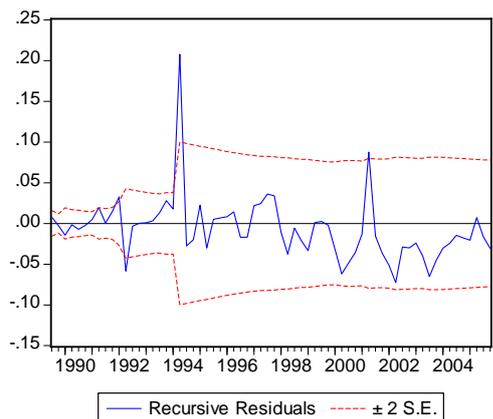
After obtaining AR(2) process for inflation, in order to ensure the reliability of the results I conduct the diagnostic tests here below. Further details of the tests may be found in appendix G.

<b>Statistical Test Results</b>				
<b>Test</b>	<b>Statistic Value</b>	<b>P-value</b>	<b>Null Hypothesis (H<sub>0</sub>)</b>	<b>Reject / Not Reject H<sub>0</sub></b>
Jarque-Bera	497.3749	0.000000	Normality	Reject
LM Test	0.785652	0.460169	No serial correlation	Not Reject
White Heteroskedasticity Test*	0.356085	0.838873	Homoscedastic	Not Reject
Chow Breakpoint Test (1996 Q1)	4.624464	0.005494	No Structural Change	Reject
Chow Breakpoint Test (2001 Q3)	5.314452	0.002498	No Structural Change	Reject
RESET Test	2.752469	0.071328	Correct Specification	Not Reject
ARCH Test	0.675298	0.414169	No ARCH Effect	Not Reject

The LM test indicates no serial autocorrelation in the residuals. Therefore, our equation is not subject to autocorrelation. Moreover, after running White Heteroskedasticity Test we also see that disturbances have constant variance. Thus, the model is not subject to heteroscedasticity as well. This can also be confirmed from the results of ARCH test.

For the Chow Breakpoint Test I used 1996 Q1 and 2001 Q3 as the breakpoints, because a huge financial crisis that happened in previous periods might have caused a structural change in the model. According to the above results I found out that there has been a structural break in the time series path of Turkish inflation. Furthermore, RESET test confirms that the model is correctly specified making us somewhat happy about the reliability of specification of our variables.

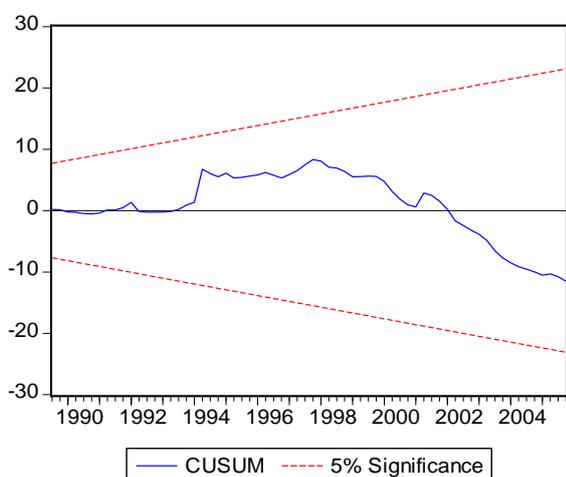
However, Jarque-Bera test shows us that residuals are not normally distributed. Since the residuals are not normally distributed we should be cautious about the reliability of the model results. Therefore, for more detailed statistical analysis I used further statistical stability tests. The tests below are conducted by specifying AR(1) and AR(2) as  $dcpi(-1)$  [ $\Delta P_{t-1}$ ] and  $dcpi(-2)$  [ $\Delta P_{t-2}$ ] respectively.



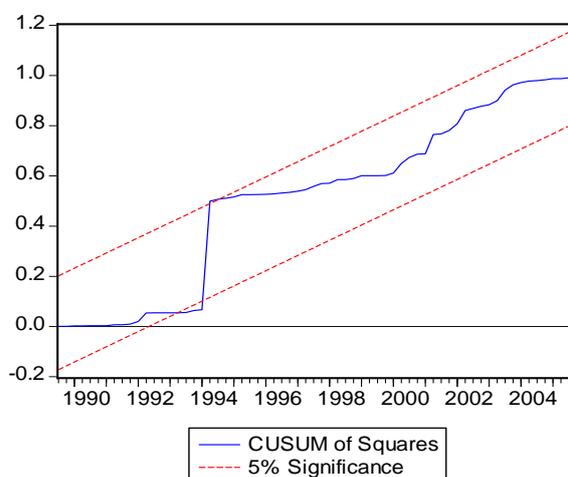
**Graph 11: Plot of Recursive Residuals  
AR(2) Model**

The plot of recursive residuals for AR(2) model of inflation shows that the parameters became unstable around 1992, 1994, and 2001 (1994 is the heaviest). One should also notice that the significance bands shown with dotted lines are larger than those of the Maliszweksi's equation. Especially, they follow an unstable model path until 1994 and become larger and more stable after this period.

The graphs below plot the cumulative sum together with the 5% critical lines. According to the graph 12 we can say that the parameters of AR(2) model are stable since the line stays in between the 5% critical lines. However, a more detailed analysis through the cumulative sum of squares show that the parameters become unstable around 1994 since they flow slightly outside the 5.00% significance band. However, they are stable for the rest of the observation period. Therefore, we might be able to obtain good forecast results by using an AR(2) model.

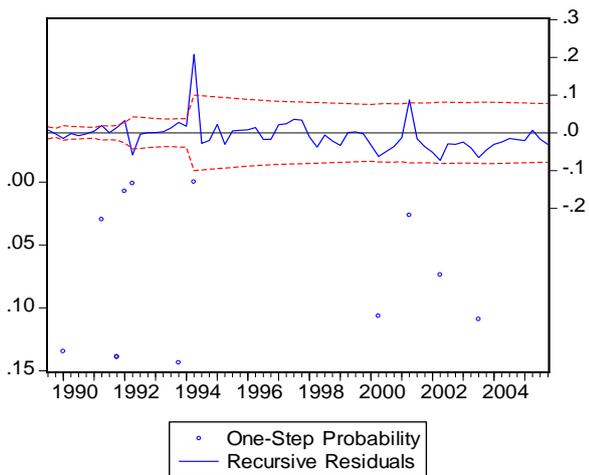


**Graph 12: Cumulative Sum – AR(2) Model**

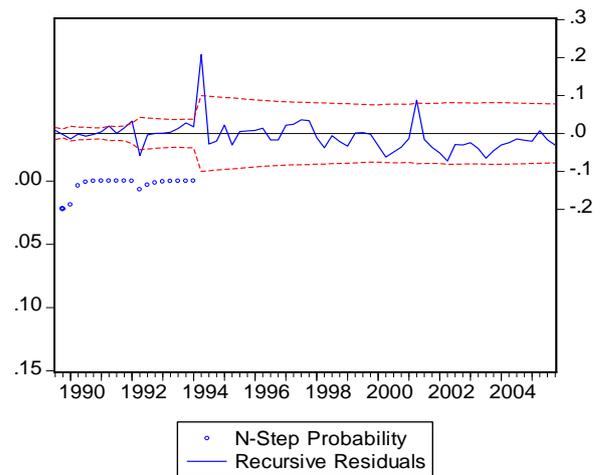


**Graph 13: Cumulative Sum of Squares – AR(2) Model**

The One-Step probability test results show that the least successful periods for the AR(2) model estimations are around years 1992, 1994, and 2000 since the points with p-values less than 0.05 correspond to those points where the recursive residuals go outside or approximate to the two standard error bounds. The N-step probability test, in line with the results of the recursive residuals, shows a structural break in the economy for the period between 1990 and 1994.



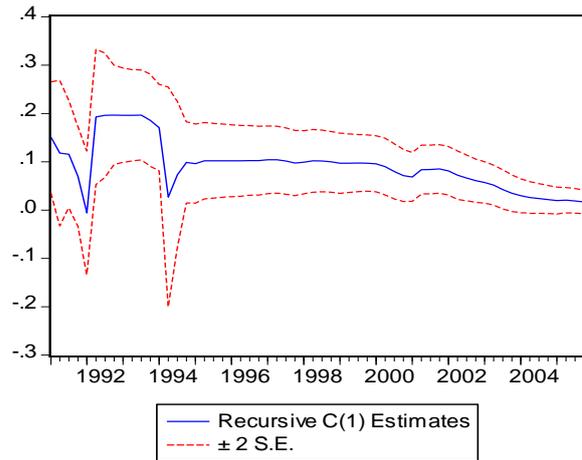
**Graph 14: One Step Probability – AR(2) Model**



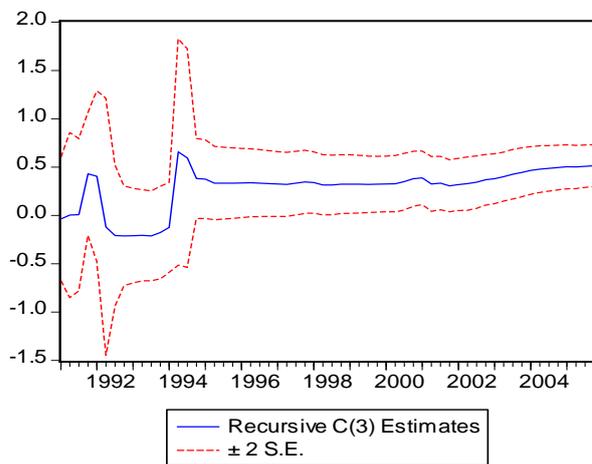
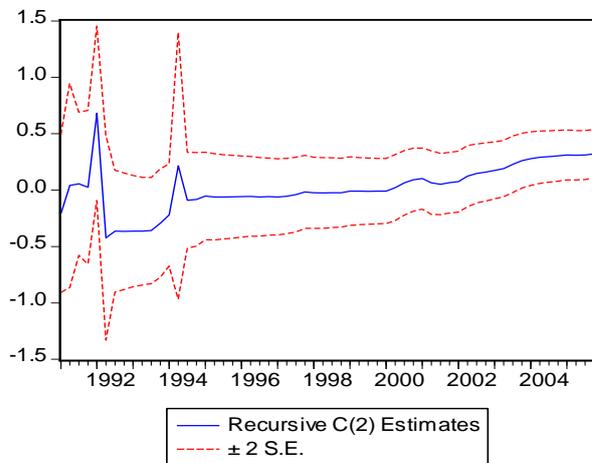
**Graph 15: N-Step Probability – AR(2) Model**

Finally, according to the recursive coefficient graphs below almost all variables have significant variances in the short run. However, they seem to stabilize in the medium-run and then again move to a new level in the long run as more data over the sample period are added. However, the change to a new level in the long run happens in a very smooth process. On the other hand, in the short run the variability in the coefficients is very high since there are significant structural breaks in the economy during those periods (as confirmed in the above tests).

**Graph 16: Recursive Coefficients – AR(2) Model**



Variable	Coefficient Indicator
<i>intercept</i>	C(1)
$\Delta P_{t-1}$	C(2)
$\Delta P_{t-2}$	C(3)



5.3.3- TAR Model

TAR model captures the non-linear form of the inflation data. Given the strict variations in Turkish inflation (as it can be seen from graph 3) and the large time intervals due to the nature of the quarterly data I choose to use TAR model. For estimation I utilized a dummy variable to capture the asymmetric pattern in inflation time series data. The threshold parameter measure for dummy variable is chosen as the quarterly average inflation rate of around 10.25%. That is;

$$Dummy = \begin{cases} 0 & \text{if } \Delta Ln(P_{t-1}) \leq 0.1025 \\ 1 & \text{if } \Delta Ln(P_{t-1}) > 0.1025 \end{cases}$$

such that :

$$\Delta Ln(P_t) = c_0 + \beta_1 \Delta Ln(P_{t-1}) + \beta_2 \Delta Ln(P_{t-2}) + dummy * (c_1 + \beta_3 \Delta Ln(P_{t-1}))$$

$$\Delta Ln(P_t) = \begin{cases} c_0^1 + \beta_1^1 \Delta Ln(P_{t-1}) + \beta_2^1 \Delta Ln(P_{t-2}) + \varepsilon_t^1 & \text{if } \Delta Ln(P_{t-1}) \leq 0.1025 \\ c_0^2 + \beta_1^2 \Delta Ln(P_{t-1}) + \beta_2^2 \Delta Ln(P_{t-2}) + \varepsilon_t^2 & \text{if } \Delta Ln(P_{t-1}) > 0.1025 \end{cases}$$

The summary of regression results in the table here below indicates that the TAR model was able to capture the asymmetry with one lags (further details may seen in appendix H). The two regime in Turkish inflation can therefore be modeled with two AR(2) processes. On the other hand, only the intercept value between the parentheses after the dummy variable is significantly different than zero.

Therefore, from the statistical findings when  $\Delta Ln(P_{t-1}) \leq 0.1025$  then the model equation become:

$$\Delta Ln(P_t) = 1.034 * \Delta Ln(P_{t-1}) + 0.303 * \Delta Ln(P_{t-2}) + \varepsilon_{t-1} \quad (1) \text{ [when } \Delta Ln(P_{t-1}) \leq 0.1025]$$

Further, when  $\Delta Ln(P_{t-1}) > 0.11$  then the model equation becomes:

$$\Delta Ln(P_t) = 0.103 + 0.033 * \Delta Ln(P_{t-1}) + 0.303 * \Delta Ln(P_{t-2}) + \varepsilon_{t-1} \quad (2) \text{ [when } \Delta Ln(P_{t-1}) > 0.1025]$$

The above equations suggest that when quarterly inflation is below the average inflation, it tend to go over the average inflation somewhat quickly as it can be understood from equation (1) and from the presence of a large number of data points over the average inflation in graph 3. That is a percentage point increase in the first and second lags of inflation causes an increase of around 1.034 and 0.303 percentage point increase respectively in the current inflation. Furthermore, when we look at the equation 2, we see that inflation builds upon the

average inflation value and tends to stay higher along with an average value of 0.103 percentage points coming from the significant intercept coefficient. This can also be understood from the previous findings on the inertial factors arising from inflationary expectations and adjustment lags in Turkish economy. However, the impact of the first inflation lag lowers to 0.033. This might suggest the capped behavior of Turkish inflation ensuring that inflation rate, though high, has never gone out of control (i.e. hyperinflation) in Turkey. Thus, the fact that an I(1) process is considered may be justified with this assertion.

**Dependent Variable:  $\Delta \text{Ln}(P_t)$**

$$\Delta \text{Ln}(P_t) = \alpha_1 + \beta_1 * \Delta \text{Ln}(P_{t-1}) + \beta_2 * \Delta \text{Ln}(P_{t-2}) + I(\Delta \text{Ln}(P_{t-1}) > 0.1025) * (\alpha_2 + \beta_3 * \Delta \text{Ln}(P_{t-1}))$$

	<b>Coefficient</b>	<b>Std. Error</b>	<b>t-Statistic</b>	<b>Prob.</b>
$\alpha_1$	-0.013254	0.018201	-0.728198	0.4691
$\beta_1$	1.033943	0.355733	2.906517	0.0050
$\beta_2$	0.302982	0.122985	2.463559	0.0165
$\alpha_2$	0.103244	0.032101	3.216257	0.0020
$\beta_3$	-1.001293	0.383035	-2.614102	0.0111

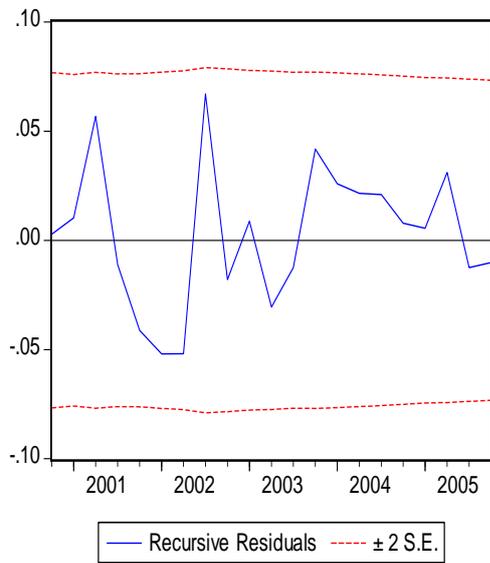
*Adjusted R-squared: 0.406895*

Given the above findings, I also ran several diagnostic tests in order to ensure the reliability of the statistical results above. The summary of the results can be seen in the table here below. Further details are provided in appendix I. Please note that RESET test and Chow Breakpoint test are skipped due to the nature of the TAR model. Instead, parameter stability tests are carried in the recursive residuals and coefficients, and cumulative sum tests.

<b>Statistical Test Results</b>				
<b>Test</b>	<b>Statistic Value</b>	<b>P-value</b>	<b>Null Hypothesis (H<sub>0</sub>)</b>	<b>Reject / Not Reject H<sub>0</sub></b>
Jarque-Bera	789.5020	0.000000	Normality	Reject
LM Test	0.207450	0.813216	No serial correlation	Not Reject
White Heteroskedasticity Test	0.210002	0.957078	Homoscedastic	Not Reject
ARCH Test	0.027171	0.869578	No ARCH Effect	Not Reject

The diagnostic test results suggest that our TAR model specification has no serial correlation and that residuals are homoscedastic. The homoscedasticity may also be understood from the ARCH test showing that there is not ARCH effect to the TAR specification of Turkish inflation. However, the Jarque-Bera test shows that the residuals are non-normally distributed suggesting that we should interpret the model results with caution. Therefore, in order to ensure more reliability I run further stability tests. During the analysis of the results one

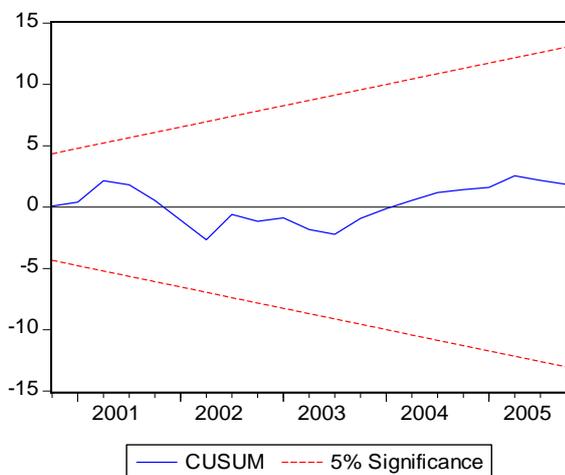
should notice that the period of observation is shorter for the TAR model due to its model specification.



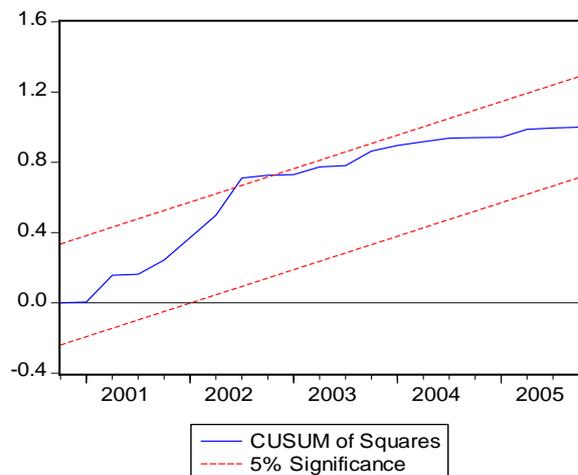
**Graph 17: Plot of Recursive Residuals  
TAR Model**

The graph of recursive residuals shows that the TAR model had a stable performance through the observation period. This may be due to the fact that TAR model captures the non-linear behavior, thus structural breaks, of inflation with its two-regime form. However, we should note that the bands depicted with dotted lines follow are wider than those in the graph of recursive residuals for Maliszweksi's equation. Thus, the stability of TAR model is confirmed at a higher critical value. On the other hand, as we move along the graph (to the right hand side) we capture a more stable pattern for the model.

The graphs below plot the cumulative sum together with the 5% critical lines for the TAR model. Here we try to find parameter instability if the cumulative sum goes outside the area between the two critical lines. According to the Cumulative Sum graph we can see the parameters are stable since the line stays in between the 5% critical lines. However, the graph of cumulative sum of squares shows that the parameters became slightly unstable during the period between 2002 and 2003.

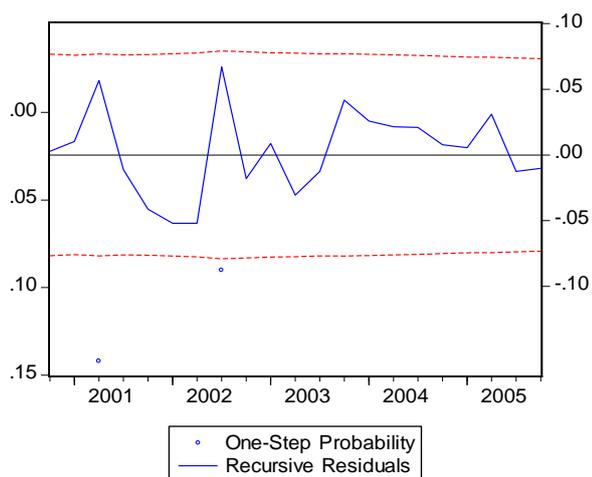


**Graph 18: Cumulative Sum – TAR Model**

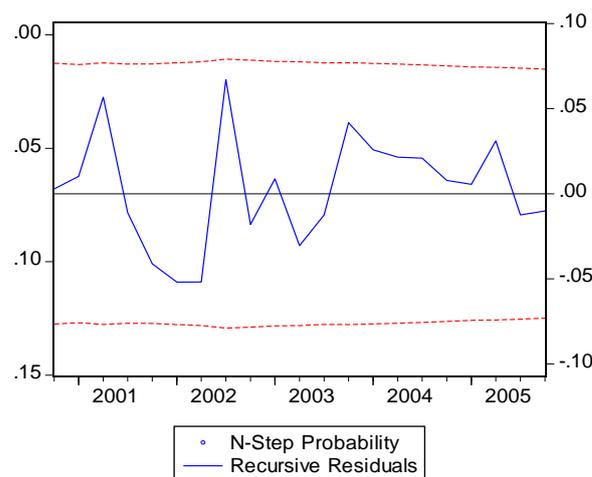


**Graph 19: Cumulative Sum of Squares – TAR Model**

Graph 20 and graph 21 are The One-Step and N-Step Probability tests results for TAR model. From the result of one-step probability we may spot the least successful periods for the TAR model around years 2001 and 2002 since the points below the recursive residuals correspond to these years. On the other hand, the n-step probability shows the most feasible cases for forecasting by carrying a multiple Chow Forecast tests. We see that a non-linear specification performs well since it captures the structural breaks in the economy.



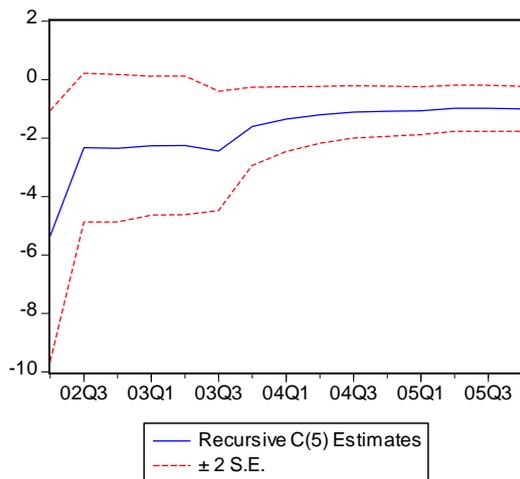
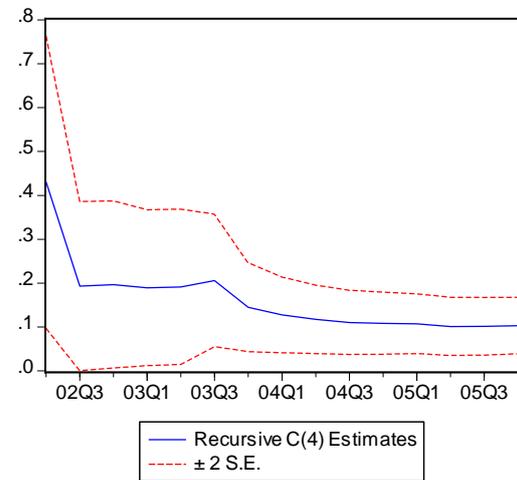
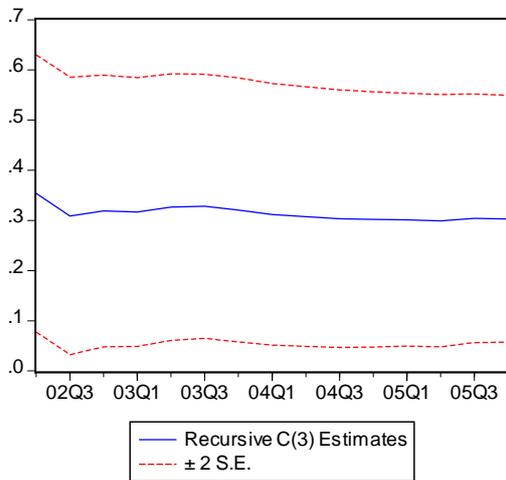
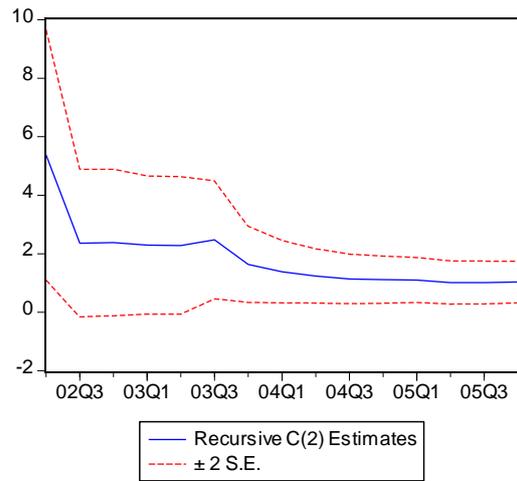
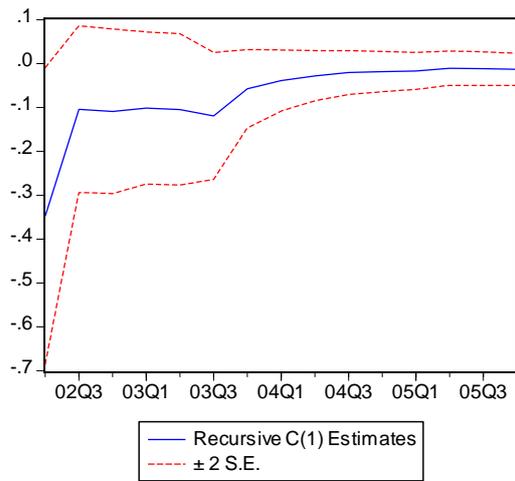
**Graph 20: One Step Probability – TAR Model**



**Graph 21: N-Step Probability – TAR Model**

Finally, according to the recursive coefficient graphs below almost all variables have significant variances in the short run as did the recursive coefficient graphs of Maliszewski's Equation. However, in the long run the variables seem to stabilize as more data over the sample period are added. The only apparent stability is seen with the coefficient of the second lag of inflation ( $\Delta P_{t-2}$ ). Though its coefficient was slightly unstable in the short run, it became stable quickly and stayed around the same level when more data over the sample period are added. On the other hand, while the impact of the coefficient of  $\Delta P_{t-1}$  lowers as more data are added, the impact of the coefficient of  $\Delta P_{t-1}$  multiplied with dummy ( $\beta_3$ ) increases. Furthermore, the paths they follow are very similar in a manner as if they were reflected from the x-axis. Furthermore, the value of the significant intercept coefficient ( $\alpha_2$ ) decreases as more data is utilized. This might basically suggest the lowering inflation inertia in Turkish economy through the observation period as the rate of inflation lowered through the end of 2005.

**Graph 22: Recursive Coefficients**



**Variable    Coefficient Indicator**

$\alpha_1$	C(1)
$\beta_1$	C(2)
$\beta_2$	C(3)
$\alpha_2$	C(4)
$\beta_3$	C(5)

#### 5.4- Forecast Results

The pseudo out-of-sample forecasts are conducted based on dynamic rolling regression starting with 1988Q1-2004Q4 as the sample period and moving one month ahead each time to generate new forecasts. That is, by using the information at the start of the period, I forecast the previous period recursively. The forecasted period is 2005Q1 and 2005Q4. Thus, the forecast horizon is one year. The reason for selecting 2005 is that the period was one of the most stable periods in the history of Turkish economy.

In order to select the best performing forecast, I compare the root mean square error (RMSE), mean absolute error (MAE) and Theil's inequality coefficient. The advantage of RMSE is that it penalizes the models with large prediction errors. On the other hand, if there is a steady trend then MAE may be used to select the best performing model. Furthermore, Theil's inequality coefficient takes values between 0 and 1, with 0 being the perfect forecast prediction.

The table below gives the summary of the results. Further results are provided in appendix J.

<b>Model</b>	<b>RMSE</b>	<b>MAE</b>	<b>Theil's Inequality Coefficient</b>
AR(2)	0.022171	0.019393	0.299714
TAR Model	0.024198	0.021333	0.608229
Maliszweksi's Equation	0.012304	0.010489	0.239326

The results above indicate that AR(2) and Maliszweksi models have good forecasting performances since the Theil's Inequality Coefficients are closer to 0 than they are to 1. However, Maliszweksi's Equation outperformed both AR(2) and TAR models. Thus, it is the best performing model. On the other hand, AR(2) model performs better than TAR model. In sum, a forecast performance taking into consideration the structure of the economy performed better than the two atheoretical models for Turkish case.

## **6- Conclusions**

The money, inflation, output and exchange rate series are found to be I(1) and are cointegrated. Thus, in the long run the price level is positively related to the growth in exchange rate, money and output. This conclusion is well in line with the theoretical suggestion, as the growth in money and output and depreciation causes an increase in inflation in the long run. On the other hand, in the short run, Turkish inflation is positively

affected by the contemporaneous depreciation and monetary and output growths ( $\Delta Ln(E_t)$ ,  $\Delta Ln(M_t)$ , and  $\Delta Ln(Y_t)$ ). Furthermore, the presence of the lags show the significance of adjustment lags in Turkish economy. The fact that both money and output growth have lags shows that Turkish inflation is prone to the impacts of earlier policies. Also, the impact of the depreciation is higher than the impact of monetary growth suggesting the exposure of Turkish economy to international effects. In addition, the presence of inflation lag confirms the inflation inertia in Turkey. In sum, the positive coefficients of the contemporaneous depreciation and monetary and output growths in the Maliszweksi's equation suggest the expansionary policy followed by Turkey throughout the years given the fact that Turkey is an emerging market.

The finding of inflation inertia by the Maliszweksi's equation is also confirmed by AR(2) and TAR model since the lagged values of inflation were significant. Furthermore, the two-regime TAR model suggests that Turkish inflation can be modeled with two AR(2) processes and that inflation tend to stay higher when it is above the average inflation rate.

In terms of stability tests the parameters of the Maliszweksi's equation were the most stable one though they may have instabilities during certain periods due to the structural breaks in the time series path of Turkish Economy. However, CUSUM tests show that the performance of the model is reliable as it stays within the 5% significance band. In addition, the results of diagnostics tests show that the results of the equation may be perceived as reliable. This is also well confirmed by the fact that Maliszweksi's equation perform better than both AR(2) and TAR models. Comparison with AR(2) model shows that Maliszweksi's equation perform better than the mostly utilized benchmark model for forecasting inflation. In addition, the better performance of Maliszweksi's equation when compared to TAR model showed that creating an atheoretical model to capture the parameter instability did not help outperform a structural model. In sum, a forecast performance taking into consideration the structure of the economy performed better than the two atheoretical models for Turkish case.

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## Appendices

### Appendix A: ADF Tests for Variables

#### *Inflation*

Null Hypothesis: D(LCPISA) has a unit root

Exogenous: Constant

Lag Length: 0 (Fixed)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.867474	0.0037
Test critical values: 1% level	-3.527045	
5% level	-2.903566	
10% level	-2.589227	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LCPISA,2)

Method: Least Squares

Date: 08/09/06 Time: 16:16

Sample (adjusted): 1988Q3 2005Q4

Included observations: 70 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LCPISA(-1))	-0.382060	0.098788	-3.867474	0.0002
C	0.042453	0.012492	3.398270	0.0011
R-squared	0.180302	Mean dependent var		-0.001315
Adjusted R-squared	0.168247	S.D. dependent var		0.048534
S.E. of regression	0.044263	Akaike info criterion		-3.369162
Sum squared resid	0.133229	Schwarz criterion		-3.304919
Log likelihood	119.9207	F-statistic		14.95736
Durbin-Watson stat	2.590320	Prob(F-statistic)		0.000249

#### *Exchange Rate*

Null Hypothesis: D(LEXSA) has a unit root

Exogenous: Constant

Lag Length: 3 (Fixed)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.398868	0.0144
Test critical values: 1% level	-3.531592	
5% level	-2.905519	
10% level	-2.590262	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LEXSA,2)

Method: Least Squares

Date: 08/09/06 Time: 16:18

Sample (adjusted): 1989Q2 2005Q4

Included observations: 67 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEXSA(-1))	-0.535120	0.157441	-3.398868	0.0012
D(LEXSA(-1),2)	-0.068949	0.162185	-0.425129	0.6722
D(LEXSA(-2),2)	0.060846	0.149052	0.408219	0.6845
D(LEXSA(-3),2)	0.193836	0.125618	1.543057	0.1279
C	0.052233	0.019480	2.681388	0.0094
R-squared	0.315634	Mean dependent var	-0.000515	
Adjusted R-squared	0.271482	S.D. dependent var	0.106392	
S.E. of regression	0.090809	Akaike info criterion	-1.888422	
Sum squared resid	0.511269	Schwarz criterion	-1.723893	
Log likelihood	68.26214	F-statistic	7.148707	
Durbin-Watson stat	1.822860	Prob(F-statistic)	0.000084	

*Money*

Null Hypothesis: D(LMSA) has a unit root

Exogenous: Constant

Lag Length: 1 (Fixed)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-4.241105	0.0012
Test critical values: 1% level	-3.528515	
5% level	-2.904198	
10% level	-2.589562	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LMSA,2)

Method: Least Squares

Date: 08/09/06 Time: 16:19

Sample (adjusted): 1988Q4 2005Q4

Included observations: 69 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LMSA(-1))	-0.669764	0.157922	-4.241105	0.0001

D(LMSA(-1),2)	-0.215214	0.119746	-1.797247	0.0769
C	0.086173	0.022283	3.867172	0.0003
R-squared	0.452820	Mean dependent var	-0.001137	
Adjusted R-squared	0.436239	S.D. dependent var	0.096672	
S.E. of regression	0.072585	Akaike info criterion	-2.365610	
Sum squared resid	0.347727	Schwarz criterion	-2.268475	
Log likelihood	84.61353	F-statistic	27.30922	
Durbin-Watson stat	2.058497	Prob(F-statistic)	0.000000	

*Output*

Null Hypothesis: D(LYSA) has a unit root

Exogenous: Constant

Lag Length: 1 (Fixed)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.455207	0.0123
Test critical values: 1% level	-3.528515	
5% level	-2.904198	
10% level	-2.589562	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LYSA,2)

Method: Least Squares

Date: 08/09/06 Time: 16:19

Sample (adjusted): 1988Q4 2005Q4

Included observations: 69 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LYSA(-1))	-0.521893	0.151045	-3.455207	0.0010
D(LYSA(-1),2)	-0.330107	0.118835	-2.777873	0.0071
C	0.061627	0.019883	3.099478	0.0028
R-squared	0.458306	Mean dependent var	-0.000346	
Adjusted R-squared	0.441891	S.D. dependent var	0.087283	
S.E. of regression	0.065206	Akaike info criterion	-2.580025	
Sum squared resid	0.280621	Schwarz criterion	-2.482890	
Log likelihood	92.01085	F-statistic	27.92000	
Durbin-Watson stat	2.177317	Prob(F-statistic)	0.000000	

## Appendix B: Regression Results for Cointegration

*Regression of inflation with money, output, and exchange rates*

Dependent Variable: DCPI

Method: Least Squares

Date: 08/09/06 Time: 16:39

Sample (adjusted): 1988Q2 2005Q4

Included observations: 71 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.011847	0.006479	1.828548	0.0719
DEX	0.228002	0.029262	7.791848	0.0000
DM	0.166749	0.041896	3.980100	0.0002
DY	0.482126	0.043000	11.21212	0.0000
R-squared	0.831478	Mean dependent var		0.113201
Adjusted R-squared	0.823932	S.D. dependent var		0.054759
S.E. of regression	0.022977	Akaike info criterion		-4.653948
Sum squared resid	0.035372	Schwarz criterion		-4.526473
Log likelihood	169.2152	F-statistic		110.1910
Durbin-Watson stat	2.058741	Prob(F-statistic)		0.000000

### *Cointegration test*

Null Hypothesis: D(ECM) has a unit root

Exogenous: None

Lag Length: 2 (Fixed)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-6.374320	0.0000
Test critical values:		
1% level	-2.599934	
5% level	-1.945745	
10% level	-1.613633	

\*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(ECM,2)

Method: Least Squares

Date: 08/09/06 Time: 16:40

Sample (adjusted): 1989Q2 2005Q4

Included observations: 67 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(ECM(-1))	-2.146379	0.336723	-6.374320	0.0000
D(ECM(-1),2)	0.420163	0.244414	1.719060	0.0904
D(ECM(-2),2)	-0.030460	0.125443	-0.242817	0.8089

R-squared	0.804159	Mean dependent var	-0.000555
Adjusted R-squared	0.798039	S.D. dependent var	0.056982
S.E. of regression	0.025608	Akaike info criterion	-4.448099
Sum squared resid	0.041969	Schwarz criterion	-4.349382
Log likelihood	152.0113	Durbin-Watson stat	1.951435

### Appendix C: Regression Results for ECM

Dependent Variable: DCPI  
Method: Least Squares  
Date: 08/09/06 Time: 15:25  
Sample (adjusted): 1988Q4 2005Q4  
Included observations: 69 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.003570	0.006737	-0.529873	0.5982
DCPI(-1)	0.512102	0.150116	3.411367	0.0012
DEX	0.190431	0.026786	7.109430	0.0000
DM	0.136917	0.034366	3.984079	0.0002
DM(-1)	-0.163175	0.046907	-3.478685	0.0010
DM(-2)	0.087252	0.035914	2.429426	0.0182
DY	0.293868	0.051233	5.735896	0.0000
DY(-1)	-0.210756	0.075688	-2.784519	0.0072
DY(-2)	-0.182205	0.036645	4.972104	0.0000
ECM(-1)	-0.400817	0.159229	-2.517235	0.0146

R-squared	0.906525	Mean dependent var	0.113253
Adjusted R-squared	0.892267	S.D. dependent var	0.055557
S.E. of regression	0.018235	Akaike info criterion	-5.037617
Sum squared resid	0.019619	Schwarz criterion	-4.713834
Log likelihood	183.7978	F-statistic	63.57642
Durbin-Watson stat	1.975175	Prob(F-statistic)	0.000000

### Appendix D: Diagnostic Test Results for the Maliszweksi's equation

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.155388	Prob. F(2,57)	0.856445
Obs*R-squared	0.374161	Prob. Chi-Square(2)	0.829377

Test Equation:  
Dependent Variable: RESID  
Method: Least Squares  
Date: 08/09/06 Time: 17:28  
Sample: 1988Q4 2005Q4

Included observations: 69  
 Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-6.03E-05	0.006856	-0.008788	0.9930
DCPI(-1)	0.006485	0.156652	0.041396	0.9671
DEX	-0.001365	0.027508	-0.049628	0.9606
DM	0.001977	0.035545	0.055616	0.9558
DM(-1)	-0.003524	0.048332	-0.072906	0.9421
DM(-2)	0.000800	0.037232	0.021475	0.9829
DY	-0.003224	0.054024	-0.059684	0.9526
DY(-1)	-0.000354	0.078164	-0.004523	0.9964
DY(-2)	-0.000134	0.037252	-0.003585	0.9972
ECM(-1)	0.010622	0.187670	0.056598	0.9551
RESID(-1)	-0.021996	0.211227	-0.104133	0.9174
RESID(-2)	-0.075255	0.136567	-0.551049	0.5838
R-squared	0.005423	Mean dependent var	-1.02E-17	
Adjusted R-squared	-0.186513	S.D. dependent var	0.016986	
S.E. of regression	0.018502	Akaike info criterion	-4.985083	
Sum squared resid	0.019513	Schwarz criterion	-4.596543	
Log likelihood	183.9854	F-statistic	0.028252	
Durbin-Watson stat	1.962375	Prob(F-statistic)	1.000000	

White Heteroskedasticity Test:

F-statistic	0.695582	Prob. F(18,50)	0.798863
Obs*R-squared	13.81808	Prob. Chi-Square(18)	0.740871

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 08/09/06 Time: 17:28

Sample: 1988Q4 2005Q4

Included observations: 69

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-9.55E-05	0.000232	-0.411459	0.6825
DCPI(-1)	0.001501	0.006075	0.247025	0.8059
DCPI(-1)^2	0.010089	0.019125	0.527516	0.6002
DEX	-0.001593	0.000930	-1.712164	0.0931
DEX^2	0.002431	0.003439	0.706966	0.4829
DM	0.000378	0.002064	0.182872	0.8556
DM^2	0.002451	0.005694	0.430481	0.6687
DM(-1)	-0.000125	0.002622	-0.047778	0.9621
DM(-1)^2	-0.002701	0.008090	-0.333814	0.7399
DM(-2)	0.002928	0.002118	1.382450	0.1730

DM(-2)^2	-0.007217	0.005145	-1.402893	0.1668
DY	-0.000177	0.002930	-0.060257	0.9522
DY^2	-0.003852	0.010082	-0.382045	0.7040
DY(-1)	-0.000248	0.002358	-0.105081	0.9167
DY(-1)^2	-0.004476	0.009787	-0.457340	0.6494
DY(-2)	0.001324	0.002065	0.641443	0.5242
DY(-2)^2	-0.001636	0.007648	-0.213921	0.8315
ECM(-1)	-0.005284	0.004019	-1.314609	0.1946
ECM(-1)^2	-0.017401	0.075431	-0.230692	0.8185

R-squared	0.200262	Mean dependent var	0.000284
Adjusted R-squared	-0.087644	S.D. dependent var	0.000376
S.E. of regression	0.000392	Akaike info criterion	-12.62144
Sum squared resid	7.69E-06	Schwarz criterion	-12.00625
Log likelihood	454.4396	F-statistic	0.695582
Durbin-Watson stat	1.770920	Prob(F-statistic)	0.798863

Chow Breakpoint Test: 1996Q1

F-statistic	2.694979	Prob. F(10,49)	0.010275
Log likelihood ratio	30.23940	Prob. Chi-Square(10)	0.000783

Chow Breakpoint Test: 2001Q3

F-statistic	2.127756	Prob. F(10,49)	0.039720
Log likelihood ratio	24.88363	Prob. Chi-Square(10)	0.005570

Ramsey RESET Test:

F-statistic	3.655705	Prob. F(1,58)	0.060821
Log likelihood ratio	4.217470	Prob. Chi-Square(1)	0.040010

Test Equation:

Dependent Variable: DCPI

Method: Least Squares

Date: 08/09/06 Time: 17:31

Sample: 1988Q4 2005Q4

Included observations: 69

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006011	0.008279	0.726038	0.4707
DCPI(-1)	0.409875	0.156279	2.622721	0.0111
DEX	0.143753	0.035813	4.013983	0.0002
DM	0.070673	0.048275	1.463967	0.1486
DM(-1)	-0.104956	0.055070	-1.905873	0.0616

DM(-2)	0.069188	0.036381	1.901799	0.0622
DY	0.207753	0.067382	3.083223	0.0031
DY(-1)	-0.140938	0.082555	-1.707190	0.0931
DY(-2)	0.151465	0.039288	3.855282	0.0003
ECM(-1)	-0.301936	0.164123	-1.839695	0.0709
FITTED^2	1.001521	0.523811	1.911990	0.0608
<hr/>				
R-squared	0.912068	Mean dependent var	0.113253	
Adjusted R-squared	0.896907	S.D. dependent var	0.055557	
S.E. of regression	0.017838	Akaike info criterion	-5.069754	
Sum squared resid	0.018456	Schwarz criterion	-4.713592	
Log likelihood	185.9065	F-statistic	60.15988	
Durbin-Watson stat	1.900556	Prob(F-statistic)	0.000000	

ARCH Test:

F-statistic	0.891000	Prob. F(1,66)	0.348649
Obs*R-squared	0.905772	Prob. Chi-Square(1)	0.341239

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 08/09/06 Time: 17:33

Sample (adjusted): 1989Q1 2005Q4

Included observations: 68 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000248	5.75E-05	4.314187	0.0001
RESID^2(-1)	0.115096	0.121933	0.943928	0.3486
<hr/>				
R-squared	0.013320	Mean dependent var	0.000281	
Adjusted R-squared	-0.001630	S.D. dependent var	0.000378	
S.E. of regression	0.000378	Akaike info criterion	-12.89435	
Sum squared resid	9.43E-06	Schwarz criterion	-12.82907	
Log likelihood	440.4080	F-statistic	0.891000	
Durbin-Watson stat	1.977530	Prob(F-statistic)	0.348649	

## Appendix E: AR(2) Correlogram

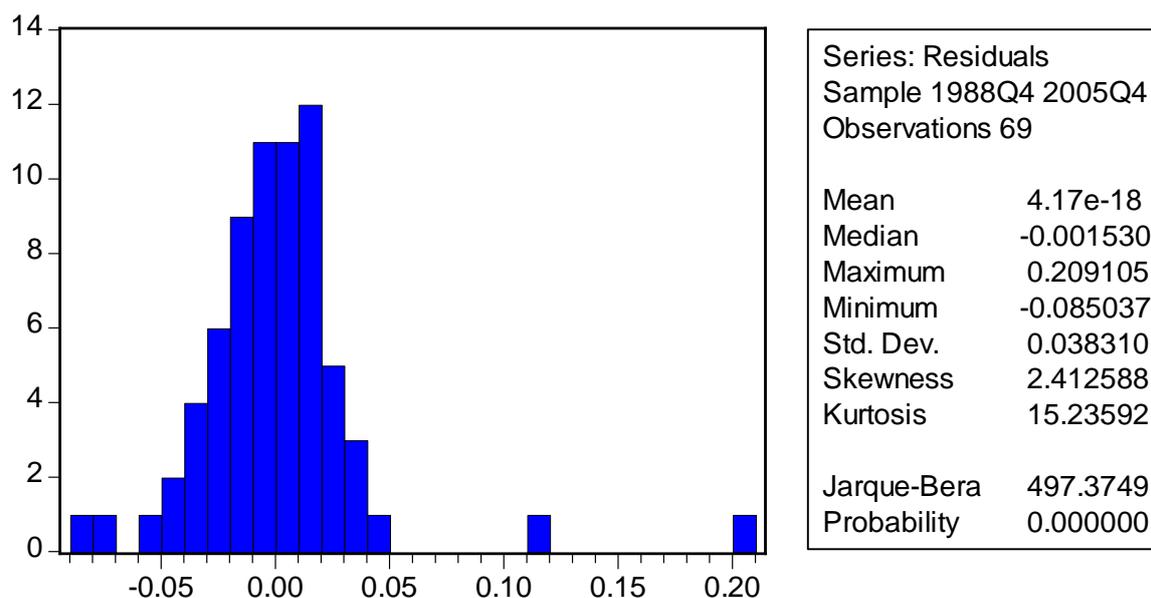
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	-0.074	-0.074	0.3983	0.528
		2	-0.040	-0.045	0.5136	0.774
		3	0.042	0.036	0.6461	0.886
		4	-0.231	-0.229	4.6843	0.321
		5	-0.004	-0.036	4.6852	0.455
		6	0.205	0.192	7.9415	0.242
		7	0.131	0.190	9.3023	0.232
		8	-0.031	-0.052	9.3803	0.311
		9	0.111	0.099	10.378	0.321
		10	-0.083	0.016	10.952	0.361
		11	-0.018	0.065	10.980	0.445
		12	0.049	-0.017	11.184	0.513
		13	0.047	0.045	11.381	0.579
		14	0.165	0.171	13.811	0.464
		15	0.061	0.085	14.154	0.514
		16	-0.017	-0.021	14.180	0.585
		17	0.036	0.072	14.303	0.646
		18	-0.107	-0.057	15.408	0.634
		19	-0.086	-0.107	16.132	0.648
		20	0.052	-0.076	16.405	0.691
		21	0.081	0.046	17.081	0.706
		22	0.086	0.069	17.858	0.714
		23	0.026	-0.055	17.931	0.761
		24	-0.118	-0.149	19.456	0.727
		25	-0.113	-0.062	20.873	0.700
		26	-0.070	-0.083	21.432	0.719
		27	-0.041	-0.134	21.630	0.756
		28	0.233	0.128	28.130	0.458

## Appendix F: AR(2) Regression Results

Dependent Variable: DCPI  
 Method: Least Squares  
 Date: 08/15/06 Time: 16:19  
 Sample (adjusted): 1988Q4 2005Q4  
 Included observations: 69 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016803	0.012271	1.369384	0.1755
DCPI(-1)	0.321797	0.107246	3.000556	0.0038
DCPI(-2)	0.514262	0.109385	4.701397	0.0000
R-squared	0.524501	Mean dependent var		0.113253
Adjusted R-squared	0.510092	S.D. dependent var		0.055557
S.E. of regression	0.038886	Akaike info criterion		-3.613840
Sum squared resid	0.099802	Schwarz criterion		-3.516705
Log likelihood	127.6775	F-statistic		36.40077
Durbin-Watson stat	2.138652	Prob(F-statistic)		0.000000

## Appendix G: Diagnostic Test Results for AR(2) process



### Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.785652	Prob. F(2,64)	0.460169
Obs*R-squared	1.653466	Prob. Chi-Square(2)	0.437476

### Test Equation:

Dependent Variable: RESID

Method: Least Squares

Date: 08/15/06 Time: 16:18

Sample: 1988Q4 2005Q4

Included observations: 69

Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.007836	0.015284	-0.512736	0.6099
DCPI(-1)	0.301717	0.309708	0.974199	0.3336
DCPI(-2)	-0.230017	0.305517	-0.752878	0.4543
RESID(-1)	-0.369841	0.321741	-1.149499	0.2546
RESID(-2)	0.089080	0.250619	0.355440	0.7234

R-squared	0.023963	Mean dependent var	4.17E-18
Adjusted R-squared	-0.037039	S.D. dependent var	0.038310
S.E. of regression	0.039013	Akaike info criterion	-3.580124
Sum squared resid	0.097410	Schwarz criterion	-3.418232
Log likelihood	128.5143	F-statistic	0.392826
Durbin-Watson stat	1.978808	Prob(F-statistic)	0.813037

White Heteroskedasticity Test:

F-statistic	0.356085	Prob. F(4,64)	0.838873
Obs*R-squared	1.502186	Prob. Chi-Square(4)	0.826254

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 08/15/06 Time: 16:18

Sample: 1988Q4 2005Q4

Included observations: 69

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000104	0.002344	0.044360	0.9648
DCPI(-1)	-0.020129	0.055369	-0.363547	0.7174
DCPI(-1)^2	0.087487	0.145578	0.600960	0.5500
DCPI(-2)	0.029415	0.057759	0.509267	0.6123
DCPI(-2)^2	-0.071630	0.152131	-0.470845	0.6394
R-squared	0.021771	Mean dependent var		0.001446
Adjusted R-squared	-0.039369	S.D. dependent var		0.005497
S.E. of regression	0.005605	Akaike info criterion		-7.460786
Sum squared resid	0.002010	Schwarz criterion		-7.298894
Log likelihood	262.3971	F-statistic		0.356085
Durbin-Watson stat	2.005972	Prob(F-statistic)		0.838873

Chow Breakpoint Test: 1996Q1

F-statistic	4.624464	Prob. F(3,63)	0.005494
Log likelihood ratio	13.73273	Prob. Chi-Square(3)	0.003292

Chow Breakpoint Test: 2001Q3

F-statistic	5.314452	Prob. F(3,63)	0.002498
Log likelihood ratio	15.56612	Prob. Chi-Square(3)	0.001392

Ramsey RESET Test:

F-statistic	2.752469	Prob. F(2,64)	0.071328
Log likelihood ratio	5.693515	Prob. Chi-Square(2)	0.058032

Test Equation:

Dependent Variable: DCPI

Method: Least Squares

Date: 08/15/06 Time: 16:20  
Sample: 1988Q4 2005Q4  
Included observations: 69

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.015201	0.024051	-0.632011	0.5296
DCPI(-1)	0.681629	0.524633	1.299247	0.1985
DCPI(-2)	1.222758	0.765219	1.597919	0.1150
FITTED^2	-7.438120	13.81149	-0.538546	0.5921
FITTED^3	8.068147	37.00488	0.218029	0.8281
R-squared	0.562161	Mean dependent var		0.113253
Adjusted R-squared	0.534797	S.D. dependent var		0.055557
S.E. of regression	0.037893	Akaike info criterion		-3.638384
Sum squared resid	0.091897	Schwarz criterion		-3.476492
Log likelihood	130.5242	F-statistic		20.54315
Durbin-Watson stat	2.008841	Prob(F-statistic)		0.000000

ARCH Test:

F-statistic	0.675298	Prob. F(1,66)	0.414169
Obs*R-squared	0.688715	Prob. Chi-Square(1)	0.406602

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 08/15/06 Time: 16:20

Sample (adjusted): 1989Q1 2005Q4

Included observations: 68 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001320	0.000696	1.895920	0.0623
RESID^2(-1)	0.100602	0.122422	0.821765	0.4142
R-squared	0.010128	Mean dependent var		0.001466
Adjusted R-squared	-0.004870	S.D. dependent var		0.005536
S.E. of regression	0.005549	Akaike info criterion		-7.521344
Sum squared resid	0.002032	Schwarz criterion		-7.456064
Log likelihood	257.7257	F-statistic		0.675298
Durbin-Watson stat	1.991457	Prob(F-statistic)		0.414169

## Appendix H: TAR Model Regression Results

Dependent Variable: DCPI

Method: Least Squares

Date: 08/15/06 Time: 12:32

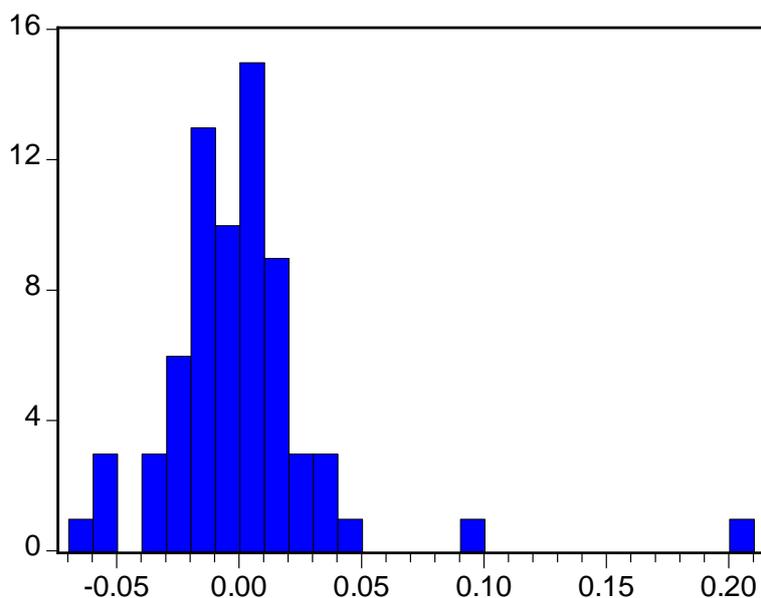
Sample (adjusted): 1988Q4 2005Q4

Included observations: 69 after adjustments

DCPI=C(1)+C(2)\*DCPI(-1)+C(3)\*DCPI(-2)+DUMPLUS\*(C(4)+C(5)  
\*DCPI(-1))

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.013254	0.018201	-0.728198	0.4691
C(2)	1.033943	0.355733	2.906517	0.0050
C(3)	0.302982	0.122985	2.463559	0.0165
C(4)	0.103244	0.032101	3.216257	0.0020
C(5)	-1.001293	0.383035	-2.614102	0.0111
R-squared	0.590916	Mean dependent var		0.113253
Adjusted R-squared	0.565348	S.D. dependent var		0.055557
S.E. of regression	0.036628	Akaike info criterion		-3.706314
Sum squared resid	0.085862	Schwarz criterion		-3.544422
Log likelihood	132.8678	Durbin-Watson stat		1.956302

## Appendix I: Diagnostic Test Results for TAR Model



Series: Residuals	
Sample 1988Q4 2005Q4	
Observations 69	
Mean	1.12e-17
Median	-0.000881
Maximum	0.207024
Minimum	-0.069779
Std. Dev.	0.035534
Skewness	2.919078
Kurtosis	18.50888
Jarque-Bera	789.5020
Probability	0.000000

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.207450	Prob. F(2,62)	0.813216
Obs*R-squared	0.458674	Prob. Chi-Square(2)	0.795061

Test Equation:

Dependent Variable: RESID

Method: Least Squares

Date: 08/15/06 Time: 12:59

Sample: 1988Q4 2005Q4

Included observations: 69

Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.000228	0.018473	-0.012367	0.9902
C(2)	0.183384	0.483601	0.379205	0.7058
C(3)	-0.118734	0.296811	-0.400032	0.6905
C(4)	0.014342	0.043373	0.330674	0.7420
C(5)	-0.172200	0.500798	-0.343851	0.7321
RESID(-1)	-0.005065	0.346722	-0.014608	0.9884
RESID(-2)	0.151245	0.285948	0.528924	0.5987

R-squared	0.006647	Mean dependent var	1.12E-17
Adjusted R-squared	-0.089483	S.D. dependent var	0.035534
S.E. of regression	0.037090	Akaike info criterion	-3.655013
Sum squared resid	0.085291	Schwarz criterion	-3.428364
Log likelihood	133.0979	Durbin-Watson stat	1.975977

White Heteroskedasticity Test:

F-statistic	0.210002	Prob. F(5,63)	0.957078
Obs*R-squared	1.131158	Prob. Chi-Square(5)	0.951309

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 08/15/06 Time: 13:00

Sample: 1988Q4 2005Q4

Included observations: 69

Collinear test regressors dropped from specification

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001333	0.002680	-0.497287	0.6207
DCPI(-1)	0.018450	0.068445	0.269561	0.7884
DCPI(-1)^2	-0.046921	0.165748	-0.283088	0.7780
DCPI(-2)	0.029053	0.055699	0.521608	0.6038

DCPI(-2)^2	-0.067031	0.146843	-0.456481	0.6496
DUMPLUS	-0.001497	0.003119	-0.479834	0.6330
R-squared	0.016394	Mean dependent var	0.001244	
Adjusted R-squared	-0.061670	S.D. dependent var	0.005245	
S.E. of regression	0.005404	Akaike info criterion	-7.520268	
Sum squared resid	0.001840	Schwarz criterion	-7.325998	
Log likelihood	265.4493	F-statistic	0.210002	
Durbin-Watson stat	2.028136	Prob(F-statistic)	0.957078	

Ramsey RESET Test:

F-statistic	2.752469	Prob. F(2,64)	0.071328
Log likelihood ratio	5.693515	Prob. Chi-Square(2)	0.058032

Test Equation:

Dependent Variable: DCPI  
Method: Least Squares  
Date: 08/15/06 Time: 16:29  
Sample: 1988Q4 2005Q4  
Included observations: 69

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.015201	0.024051	-0.632011	0.5296
DCPI(-1)	0.681629	0.524633	1.299247	0.1985
DCPI(-2)	1.222758	0.765219	1.597919	0.1150
FITTED^2	-7.438120	13.81149	-0.538546	0.5921
FITTED^3	8.068147	37.00488	0.218029	0.8281
R-squared	0.562161	Mean dependent var	0.113253	
Adjusted R-squared	0.534797	S.D. dependent var	0.055557	
S.E. of regression	0.037893	Akaike info criterion	-3.638384	
Sum squared resid	0.091897	Schwarz criterion	-3.476492	
Log likelihood	130.5242	F-statistic	20.54315	
Durbin-Watson stat	2.008841	Prob(F-statistic)	0.000000	

ARCH Test:

F-statistic	0.027171	Prob. F(1,66)	0.869578
Obs*R-squared	0.027982	Prob. Chi-Square(1)	0.867150

Test Equation:

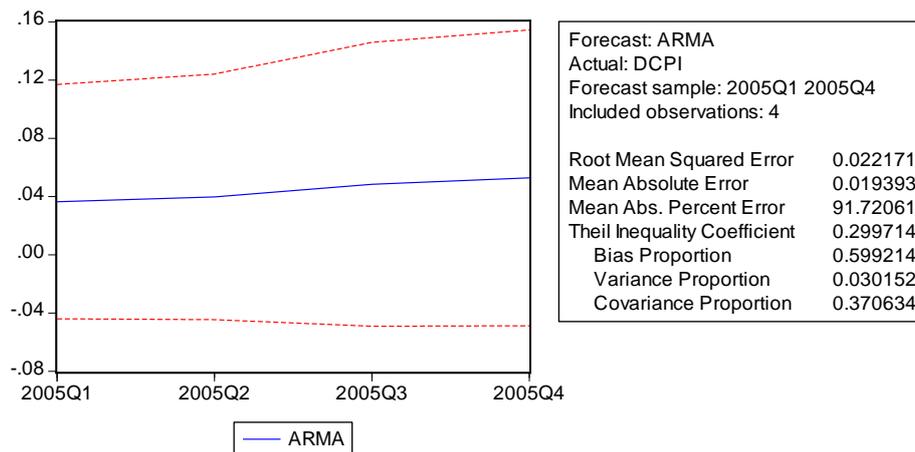
Dependent Variable: RESID^2  
Method: Least Squares  
Date: 08/15/06 Time: 13:00

Sample (adjusted): 1989Q1 2005Q4  
 Included observations: 68 after adjustments

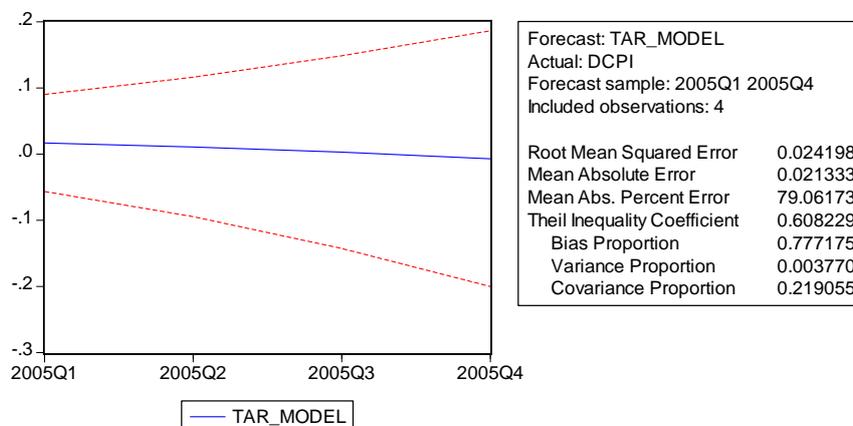
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001288	0.000664	1.940125	0.0566
RESID^2(-1)	-0.020285	0.123063	-0.164835	0.8696
R-squared	0.000412	Mean dependent var		0.001262
Adjusted R-squared	-0.014734	S.D. dependent var		0.005282
S.E. of regression	0.005321	Akaike info criterion		-7.605418
Sum squared resid	0.001869	Schwarz criterion		-7.540138
Log likelihood	260.5842	F-statistic		0.027171
Durbin-Watson stat	2.001386	Prob(F-statistic)		0.869578

## Appendix J: Forecast Results

### AR(2)



### TAR Model



### Maliszewski's Equation

