INFLATION MODELING

Sinan Bekar

111624002

İSTANBUL BİLGİ ÜNİVERSİTESİ

SOSYAL BİLİMLER ENSTİTÜSÜ

FİNANSAL EKONOMİ / SAYISAL FİNANS

YÜKSEK LİSANS PROGRAMI

Yard. Doç. Dr. Haluk Yener

2015

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ENFLASYON MODELLEMESİ

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Yard. Doç. Dr. Haluk Yener (Tez Danışmanı)	: ....
Doç. Dr. Cenktan Özyıldırım (Jüri Üyesi)	: ....
Yrd. Doç. Dr. Ebru Reis (Jüri Üyesi)	: ....

Tezin Onaylandığı Tarih	: 27.01.2015
Toplam Sayfa Sayısı	: 62

Anahtar Kelimeler (Türkçe)	Anahtar Kelimeler (İngilizce)
1) Enflasyon Modellemesi	1) Inflation Modeling
2) Enflasyon Tahmini	2) Inflation Forecasting
3) Zaman Serileri Analizi	3) Time Series Analysis
4) Makroekonometri	4) Macroeconometrics
5) Maliszewski'nin Denklemi	5) Maliszewski's Equation

ACKNOWLEDGMENTS

I would like to thank my thesis advisor Asst. Prof. Dr. Haluk Yener for his kindness and forbearance. I am really thankful for his tolerant guidance and encouragements. I am thankful for having the chance to work with him.

I also would like to thank my friend Fuat Can Beylunioğlu who help me on Eviews and R package program in this study.

Finally, I am so grateful to my family for their motivation during the thesis period and I am really indebted to my family for their endless support. They always encourage and support me in all my stressful times. Therefore, I am dedicating this thesis to my great family.

ÖZET

Bu tez, Haluk Yener'in 2006 yılında yaptığı Enflasyon Modellemesi yüksek lisans tezinin üzerine kurulmuş ve kendisinin literatüründen ve genel yaklaşımından faydalanılmıştır. Asıl amaç, gelişmekte olan ülke ekonomilerinin enflasyon tahmini için tasarlanan ve Gürcistan'ın enflasyon modellemesi için kullanılan Maliszewski Denkleminin, son yıllarda istikrarlı bir ekonomiye sahip olan Türkiye Cumhuriyeti'nin enflasyon tahmini için, bir teorik model olarak ateorik modellere kıyasla performansını yeniden test etmektir. Daha önceden yapmış olduğu çalışmasında, Yener (2006) ateorik modeller olan AR(2) ve TAR modellere kıyasla, Maliszewski Denkleminin 1988-2006 yılları arasında daha iyi bir performansa sahip olduğunu göstermiştir. Ancak, bu tezde 1999-2013 yılları arasında yaptığımız çalışmada, Maliszewski, diğer iki ateorik modele göre daha kötü bir performans göstermiştir. Bulgulardaki bu farklılığın nedenlerinden bir tanesini Türkiye'nin son on senedeki isktikrarlı ekonomik yapsını gösterebiliriz.

ABSTRACT

This thesis is built on Haluk Yener's (2006) master thesis which is called Inflation Modelling and benefited from his literature and general framework[1]. Main purpose is to test again Maliszewski Equation, previously developed for estimating emergent market economies' inflation and was also applied to Georgia's inflation, for Turkey's inflation forecast which has stabile economic structure in recent years, as a theoretical model for comparing with atheoretical models. The previous study by Yener (2006) found that Maliszewski Equation had the best performance when compared to the atheoretical models AR(2) and TAR through the observation period of 1988-2006. However, in this study, we found that it has worst performance in comparison with AR (2) and TAR model within the observation period of 1999-2013. As one of the main reasons that changed the previous results, we may suggest Turkey' stabile economic structure in the last decade.

[1] Haluk Yener (2006), Thesis (MSc.)-Bilgi University. Institute of Social Sciences, Bilgi Library Catolog

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ILLUSTRATIONS

1) INTRODUCTION

The number of inflation forecast models in the literature is exhaustive as inflation is an important instrument for government politics, economic stability and future economic decisions, etc. Therefore, this thesis first reviews many inflation studies which include inflation modeling and forecasts. In addition to these, its purpose is to forecast inflation in Turkey via the application of theoretical and atheoretical econometric models. To this end, this thesis compares the inflation forecasts of Turkey obtained by the use of Maliszewski's Model with the use of other two atheoretical time series models which are namely AR(p) and TAR models. As we will explain more thoroughly in the following sections, Maliszewski Equation (2003) was first developed by Wojciech Maliszewski to estimate emergent market economies' inflation and it was also used for Georgia's inflation modeling[2].

2) GENERAL FRAMEWORK AND COMMON APPROACH

Inflation is defined as a sustained increase in the aggregate or general price level in an economy. In other words, inflation means that there is an increase in the cost of living. Therefore, forecasting inflation is a very important issue for future investment and saving decisions. Hence, econometricians or economists who try to estimate inflation and according to structure of economics, generally use three models to forecast inflation. These are respectively, atheoretical linear or non-linear time series models, structural models based on an economic theory, and surveys that measure the expectations of agents in an economy.

2.1) Definition of Variables

Generally, the change in the price level is obtained using Consumer Price Index (CPI). Therefore, the change in CPI is used as a dependent variable to measure inflation. On the other hand, the independent variables that we use to forecast inflation may be categorized under three types: First one are the nonfinancial macro indicators which are mainly consumption, investment, unemployment rates, money supply etc. Second are the financial variables which are interest rates, default spreads, exchange rates, etc. Finally, a third type are the surveys of inflation expectations which are obtained from opinions of professional forecasters, households and firms. As a result, according to structure of economy, there are a lot of options to predict inflation and in the thesis when constructing the theoretical model we benefit from financial and non-financial variables to forecast inflation which is defined as the quarterly percentage change in CPI.

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[2] Wojciech Maliszewski (2003), "Modeling Inflation in Georgia" Applied Economics. April, 2009, Vol. 41 Issue 10, p1203, 11 p.

2.2) Description of Models and Model Selection Methods

2.2.1) Description of Models[3]

The theoretical models generally have been improved with non-stochastic mathematical entities and have been implemented via the use of the empirical data and the addition of a stochastic error to the mathematical model[4]. In short, the model is formed between inflation and economic indicators through their causality relationships. However, such procedure may have its own disadvantages as the causality may be spurious. That is, as Granger and Newbold (1974) showed, there may be a spurious relationship between two unrelated variables with random walk pattern[5]. The main purpose of the study was to destroy stochastic trends in the time series, because stochastic trends cause non-stationarity in economic time series. In an earlier study, Box and Jenkins (1970) proved that the trend could be suspended with differencing the time series. Therefore, when the trend is taken away with first differencing, variable becomes I(1) stationary. Hence, Augmented Dickey Fuller (ADF) test, which is found by Dickey and Fuller in 1979, or series of other tests are used to test the variable for stationarity. In general, many economic series are found to be I(1). That is, many of them include stochastic trend and may be converted to stationary variables with first differencing.

Furthermore, Box and Jenkins method also introduced the error correction models (ECMs)[6]. Mainly thanks to ECMs, the autoregressive distributive lag (ARDL) models could be written in the error-correction form. In summary, we eliminate spurious relations from structural model with ECM and cointegration estimation as we know from Engle and Granger (1987) that variables of models built under ECM approach were also said to cointegrate. Box and Jenkins's approach led to the birth of new models for the time series. These are mainly called ARIMA (Auto Regressive Integrated Moving Average) time series. When applying them for forecasting inflation we observe that ARIMA models consider the forecasted inflation as a function of its past values, which are also called lagged variables. Therefore, we can say that these models aim to capture the memory in a time series and may also be useful

[3] The mathematical interpretation of models may be found at the end of this section.
[4] Katrina Juselius (2002), "Model and relations in economics and econometrics, "Macroeconomics and the real world: Econometric Techniques and Macroeconomics, Volume1.
[5] 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.
[6] Katrina Juselius (2002), "Model and relations in economics and econometrics, "Macroeconomics and the real world: Econometric Techniques and Macroeconomics, Volume1.

for short term forecasting. However, in optimal forecasts, the estimation may diverge as the time horizon becomes more distant. Apparently, the divergence impedes the predicting ability of the model. A method to address the problem is then to take into consideration the effect of other economic variables in inflation forecasting. In this case, we refer to VAR models since they are useful for measuring the simultaneous or joint relation of the historical variables. In addition, to understand the direction of the relation among the variables we may use Granger Causality Test (see Granger (1969)). In the VAR model, the time series characteristics of variables in terms of their lag lengths can be taken into consideration. In, this case, the model is expressed as VAR(p), where p gives the lag length. Once the VAR model is constructed, we may then use vector error-correction model (VECM) to control whether the results are due to spurious relation.

Although VAR and ARIMA may be used to forecast inflation, because they do not capture the non-linearity in data or uneven effect of serious economic shocks, they may yield poor results. Therefore, we may need to refer to other methods which capture structural breaks in the economy. These models are classified as regime switching models which are respectively Threshold Autoregressive Models (TAR), Smooth Threshold Autoregressive Models (STAR), Markov Switching Models and Neural Networks Models. Furthermore, besides linear and non-linear forecast models, combination of forecasting models are also used to forecast inflation. The combination may be the outcome of either only linear or non-linear models or both. In addition to econometric models, surveys are also used to estimate inflation and they include sample households, firms and professional forecaster's inflation expectations. The Livingston Survey, The Survey of Professional Forecasters (SPF), the Michigan Survey, and European Commission's Harmonized Consumer Survey are among the famous surveys for the inflation expectations. Generally, mean or median of the data are used to obtain survey results.

In short, we have many options to forecast inflation. According to economic structure, there are a lot of advantages or disadvantages for every model. Therefore, to decide which model is the best to forecast inflation is not a trivial task. As evident in what follows (see also Yener (2006)) finding an appropriate model for forecasting inflation even in atheoretical models is not easy as there are many to consider.

General ARMA Models *(example: ARMA(p, q))*	$r_t = \phi_o + \sum_{i=1}^{p} \phi_i r_{t-i} + a_t - \sum_{i=1}^{q} \theta_i a_{t-i}$ 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.
VAR Model *(example: Bivariate case)*	$r_{1t} = \phi_{10} + \Phi_{11} r_{1,t-1} + \Phi_{12} r_{2,t-1} + a_{1t}$ $r_{2t} = \phi_{20} + \Phi_{21} r_{1,t-1} + \Phi_{22} r_{2,t-1} + a_{2t}$ $r_t = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix}$ $r_t = \phi_0 + \Phi r_{t-1} + a_t$ where Φ is a n x n matrix, and $\{a_t\}$ is a sequence of serially uncorrelated random vectors with mean zero and covariance matrix Σ.
TAR Model *(Example: two regime TAR model with order (p_1, p_2), denoted by TAR(p_1, p_2; d, r).)*	$Y_t = \begin{cases} \beta_0^1 + \beta_1^1 Y_{t-1} + \ldots + \beta_{p1}^1 Y_{t-p1} + \varepsilon_t^1 & if\, Y_{t-d} \le r \\ \beta_0^2 + \beta_1^2 Y_{t-1} + \ldots + \beta_{p2}^2 Y_{t-p2} + \varepsilon_t^2 & if\, Y_{t-d} > r \end{cases}$ Where { ε_t^i } for i=1, 2,.. is the innovation process with variances σ_1^2 and σ_2^2. d is the delay and r is the threshold parameters.
STAR Model	$x_t = c_o + \sum_{i=1}^{p} \phi_{0,i} x_{t-i} + F\left(\frac{x_{t-d} - \Delta}{s}\right)\left(c_1 + \sum_{i=1}^{p} \phi_{1,i} x_{t-i}\right) + a_t$ Where d is the delay parameter, Δ and s are parameters representing the location and scale of model transition, and F(.) is a smooth transition function. Usually F(.) is considered a logistic, exponential or a cumulative distribution function. Mainly STAR is a weighted linear combination of the below two models: $\mu_{1t} = c_0 + \sum_{i=1}^{p} \phi_{0,i} x_{t-i}$ $\mu_{2t} = (c_0 + c_1) + \sum_{i=1}^{p} (\phi_{0,i} + \phi_{1,i}) x_{t-i}$ The weights are determined in continuous manner by

	the F(.) function.
Markov-switching Model *(Example: two-state Markov-switching model.)*	$x_t = \begin{cases} c_1 + \sum_{i=1}^{p} \phi_{1,i} x_{t-i} + a_{1t} & if\ s_t = 1 \\ c_2 + \sum_{i=1}^{p} \phi_{2,i} x_{t-i} + a_{2t} & if\ s_t = 2 \end{cases}$ The transition is driven by a hidden two-state Markov chain. s_t may take values in {1,2} and is a first order Markov chain with probabilities: $P(s_t = 2 \mid s_{t-1} = 1) = w_1$ and $P(s_t = 1 \mid s_{t-1} = 2) = w_2$ The innovational series $\{a_{1t}\}$ and $\{a_{2t}\}$ are sequences of i.i.d. random variables with mean zero and finite variance and are independent of each other. A small w_i means that the model tends to stay longer in state i, given that 1/ w_i is the expected duration of the process to stay in state i.
Artificial Neural Network Models	$v_t = \beta_0' \varsigma_t + \sum_{i=1}^{n_1} \gamma_{1i} g(\beta_{1i}' \varsigma_t) + u_{t+h}$ (a single layer ANN) where g(z) is the logistic function, $g(z) = \frac{1}{(1+e^z)}$. When y_t is modeled in levels then, $y_{t+h} = v_{t+h}$ and $\varsigma_t = \lfloor 1 \quad y_t \quad \ldots \quad y_{t-p+1} \rfloor$. When y_t is modeled in differences $y_{t+h} - y_t = v_{t+h}$ and $\varsigma_t = \lfloor 1 \quad \Delta y_t \quad \ldots \quad \Delta y_{t-p+1} \rfloor$. If we would like to use two layers then we obtain ANN with two layers in the below form: $v_t = \beta_0' \varsigma_t + \sum_{j=1}^{n_2} \gamma_{2j} g\left(\sum_{i=1}^{n_1} \beta_{2ji} g(\beta_{1i}' \varsigma_t) \right) + u_{t+h}$

2.2.2) Model Selection Methods

Deciding among the models lie in forecast evaluation. First, we need some statistical measures to ensure significance of explanatory variables, because we know from previous section that we expect to establish a relationship between inflation and other explanatory variables. Then, once an in-sample measure is established and the model is created, its out-of-sample performance should be measured[7]. As a result, root mean square error (RMSE) or mean square forecast error (MSFE) measures are used for the comparison. The application is done via the selection of a benchmark model, and if the ratio of the candidate model with the benchmark model is smaller than 1 and close to zero, then the candidate model is perceived to perform well. Additionally, we may also consider two further measures which may be taken as complementary to the aforementioned measure. These are mainly the forecast direction (M. Hashem Pesaran and Spyros Skouras 2002, McCracken and West 2002) and time distance criterion (Clive W.J. Granger, Yongil Jeon 2003). In forecast direction, as evident form its name, the capacity of the model to forecast the direction of the inflation is measured, while in the time distance the horizontal distance between the forecasted and the actual series is measured. We refer the reader to articles for further information.

3) LITERATURE REVIEW

In this section we review a number of studies that are relevant for this thesis. For an exhaustive review of the studies that are published until 2006 we refer the readers to Yener (2006). Here, we concentrate on studies that are published after 2006.

As we previously mentioned, inflation forecast studies rely on three types of models which are mainly theoretical models, atheoretical models and surveys of inflation expectations of businesses and households. Each approach is developed with the aim of increased robustness in forecasts. Nevertheless, there is still no conclusive evidence upon which approach consistently performs better than the other. Therefore, each still has its place in the literature and their performances rely upon the period and the country considered for a forecasting study.

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[7] 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.

For example, in their atheoretical study, Sezgin and Çoker (2007) studied Turkish inflation forecast using Bayesian Vector Auto-regression (BVAR) models. In their study, they also compared BVAR models with Vector Autoregression (VAR) model in two different periods that are selected as January 1986 – December 2001 and January 1986 – December 2000. Within these periods seven different BVAR models are constructed, and then the forecast performances of these, for years 2002 and 2001 are compared with VAR model. Consequently, they found that the forecast performances of BVAR models are not better than VAR models for January 2002 – December 2002 period. The reason for this can be explained by the economic crisis happened at 2001. With this respect, another model is constructed for January 1986 - December 2000 period and the January 2001 - December 2001 forecasts are examined. Finally the results showed that, "BVAR models are much better than VAR models for estimating the real values of 2001"[8].

By the application of similar technique Österholm (2008) investigated that whether the forecasting performance of Bayesian autoregressive and vector autoregressive models can be improved by incorporating prior beliefs on the steady state of the time series in the system. Therefore, he compared traditional methodology with the new framework—in which a mean-adjusted form of the models is employed—by estimating the models on Swedish inflation and interest rate data from 1980 to 2004. His results showed that the out-of-sample forecasting ability of the models is practically unchanged for inflation but significantly improved for the interest rate when informative prior distributions on the steady state are provided. Consequently, according to his study results, he said that "this new methodology could be useful since it allows us to sharpen our forecasts in the presence of potential pitfalls such as near unit root processes and structural breaks, in particular when relying on small samples"[9].

The structure of the VAR models also help us to understand the pass-through effects of exchange rate changes on the domestic prices. Görmüş and Peker (2008) showed this effects in the Turkish Economy using vector autoregression (VAR) analysis. According to their empirical evidence, they said that "the exchange rate shocks explain about 72 percent of the forecast error variance of prices in the medium and long-term horizons. Therefore, the

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8 Funda Sezgin, Elif Çoker (2007), "Analysing the Inflation in Turkey with Bayesian Vector Autoregression Models" , Marmara University Social Sciences Institute Journal, June 2007, Vol.7, p.287-300.

9 Par Österholm (2008), "Can Forecasting Performance be Improved by Considering the Steady State? An Application to Swedish Inflation and Interest Rate", Journal of Forecasting, Jan.2008, Vol.27, p41-51. 11p.

exchange rate is an important source of forecast error variance in domestic inflation”[10]. Given this evidence, we account for the effect of the exchange rate to Turkish inflation by using the theoretical model of Maliszewski (2003).

In another pass-through study regarding the Turkish Economy, Akçağlayan and Civcir (2010) measured the monetary policy reaction functions of the Central Bank of Republic of Turkey (CBRT) over the periods 1987:01–2001:12 and 2002:01–2009:05. This study investigated how the monetary policy responded to the exchange rate shocks before and after adoption of inflation targeting regime and how large the effect of exchange rate shocks is accounted for in forecast error variances decompositions for monetary policy as compared to other shocks, using the VAR model. In the end, they showed that “there has been strong pass-through during whole period. Moreover, in the post crisis period, exchange rate has been the main reaction variable for the Central Bank of Republic of Turkey”[11].

Thus, via VAR models we observe the effect of various macro variables on the Turkish Economy, especially on forecasting the Turkish inflation. In fact, (consider the relationship between the interest rate and inflation) Kaya (2013) investigated that the yield curve forecasting performance of Dynamic Nelson–Siegel Model (DNS), affine term structure VAR model (ATSM VAR) and principal component model in Turkey. He also investigated the role of macroeconomic variables in forecasting the yield curve. As a result, he reached very important results such as “Macroeconomic variables are very useful in forecasting the yield curve.” Second, “The forecasting performances of the models depend on the period under review.” Third, “considering the structural break which associates with change in monetary policy leads models to produce better forecasts than the random walk”.

While the abovementioned studies are examples for the application of VAR type models, we observe in the literature studies that rely upon the complex use of stochastic modelling. For example, Koop and Potter (2007) developed a new approach to change-point modeling which allows the number of changepoints in the observed sample to be unknown, assuming regime durations have a Poisson distribution. Their model approximately nests the two most common approaches: the time-varying parameter (TVP) model with a change-point every period and the change-point model with a small number of regimes. They focused on

[10] Şakir Görmüş, Osman Peker (2008), “Inflationary Effects of Exchage Rate’s in Turkey” , Suleyman Demirel University The Journal of Faculty of Economics and Administrative Sciences, July 2008, Vol.13 No.2 p.187-202
[11] Irfan Civcir, Anıl Akçağlayan (2010), “Inflation targeting and the exchange rate: Does it matter in Turkey?” Journal of Policy Modeling; May 2010, Vol. 32, Issue 3, p339-354. 16p.

considerable attention on the construction of reasonable hierarchical priors both for regime durations and for the parameters that characterize each regime. A Markov chain Monte Carlo posterior sampler is constructed to estimate a version of their model which allows for change in conditional means and variances. As a result, they showed how real-time forecasting can be done in an efficient manner using sequential importance sampling. According to their study, they said that "their techniques were found to work well in an empirical exercise involving U.S. GDP growth and inflation. Empirical results suggested that the number of change-points were larger than previously estimated in these series and the implied model was similar to a TVP (with stochastic volatility) model"[12].

Another alternative to VAR models is the use of Artificial Neural Networks for forecasting inflation. Erilli, Eğrioğlu, Yolcu, Aladağ, Uslu (2010) tried to check the predictions which have been obtained using the feed forward and recurrent Artificial Neural Network (ANN) for the Consumer Price Index (CPI). At the end of their study, they suggested that "new combined forecast has been proposed based on ANN in which the ANN model predictions employed in analysis were used as data"[13]. The reason for their suggestions is that they found some difference for July 2007, February 2008 and June 2008 between actual inflation value and forecasted inflation value in their model. As a result, they showed sensible reasons for these differences such as 2007 general domestic elections of Turkey, increasing prices of food and energy, persistently increasing oil prices and increasing electric and natural gas prices.

The above study is interesting as it suggests a combination of the forecasts. In another study as well, employed for the US inflation forecasts, the combination of the forecasts performed pretty accurately. Wright (2009) tried to forecast US inflation using Bayesian Model averaging. He said about his study that "I consider using Bayesian model averaging for pseudo out-of-sample prediction of US inflation, and find that it generally gives more accurate forecasts than simple equal-weighted averaging. This superior performance is consistent across subsamples and a number of inflation"[14].

[12] Garry Koop, Simon M. Potter (2007), "Estimation and Forecasting in Models with Multiple Breaks" , Review of Economic Studies, July 2007, Vol.74, Issue 3, p763-789, 27p.

[13] N. Alp Erilli, Erol Eğrioğlu, Ufuk Yolcu, Ç. Hakan Aladağ, V. Rezan Uslu (2010), "Forecasting of Turkey Inflation with Hybrid of Feed Forward and Reccurrent Artifical Neural Networks" Doğuş University Journal; Jan 2010, Vol.11, Issue 1, p42-55. 14p.

[14] Jonathan H. Wright (2009), "Forecasting US Inflation by Bayesian Model Averaging" , Journal of Forecasting, March 2009, Vol.28, Issue 2, p131-144. 14p.

Furthermore, combination of theoretical and atheoretical models may provide accurate estimates as well because it helps reduce the forecast errors. Öğünç, Akdoğan, Başer, Gülenay Chadwick, Ertuğ, Hülagü, Kösem, Özmen, Tekatlı (2013) employed that univariate models, decomposition based approaches (both in frequency and time domain), a Phillips curve motivated time varying parameter model, a suite of VAR and Bayesian VAR models and dynamic factor models for producing short term forecasts for the inflation in Turkey. Eventually, they found that "the forecast combination leads to a reduction in forecast error compared to most of the models, although some of the individual models perform alike in certain horizons"[15].

However, when forecasting inflation rather than taking combinations of country-wide forecasts, we may also consider province level inflation forecasts and use them to cope with the country-wide inflation. Tunay (2010) studied Turkey's province-based inflation using space-time autoregressive moving average (STARMA) models. Findings obtained from Tunay's study showed that statistically significance level and explanatory power of model are both expressively high. Consequently, this model can be used for forecasting province-based inflation. Therefore, Tunay said that "political authorities can easily forecast inflation and thereby take necessary measures to cope with both province-based and country-wide inflation. As a result of these, success of executed policies will undoubtedly increase"[16].

Another method, as we mentioned in the previous sections, is to use surveys. Şahinöz and Hülagü (2012) studied that inflation expectation errors to measure inflation uncertainty in Turkey by analyzing the Central Bank of Turkey Survey of Expectations data and investigates whether the disagreement among the survey participants can be used as a proxy for inflation uncertainty. They said that "disagreement seems to be a good proxy for inflation uncertainty for the 2001-2006 period while this relationship vanishes with the full-fledged inflation targeting regime after 2006"[17].

In fact, more complex theoretical approaches may be used along with surveys. Mainly, Chernov and Mueller (2012) tried to estimate a factor hidden in the nominal yield curve using

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[15] Fethi Öğünç , Kurmaş Akdoğan, Selen Başer, Meltem Gülenay Chadwick, Dilara Ertuğ, Timur Hülagü, Sevim Kösem, Mustafa Utku Özmen, Necati Tekatlı (2013), "Short-term inflation forecasting models for Turkey and a forecast combination analysis" , In Economic Modelling; July 2013, Vol. 33, p312, 14p.

[16] K. Batu Tunay (2010), "Starma Modeling and Estimation of Province-Based Inflation in Turkey" , Hacettepe University Economics and Administrative Faculty Journal, Jan 2010, Vol.28 p.1-36

[17] Timur Hülagü and Saygın Şahinöz (2012), "Is Disagreement a Good Proxy For Inflation Uncertaininty? Evidence from Turkey" , Central Bank of the Republic of Turkey, Central Bank Review; Jan 2012, Vol. 12, pp.53-62

information in the term structure of survey-based forecasts of inflation. Therefore, they constructed a model that accommodates forecasts over multiple horizons from multiple surveys and Treasury real and nominal yields by allowing for differences between risk-neutral, subjective, and objective probability measures. After that, they established that model-based inflation expectations are driven by inflation, output, and one latent factor. Consequently, they said that about their study and results. "We show that this hidden factor is not related to either current and past inflation or the standard set of macro variables studied in the literature. Consistent with the theoretical property of a hidden factor, our model outperforms a standard macro-finance model in its forecasting of inflation and yields"[18].

Finally, recently, by using a different model than those aforementioned above, Monteforte and Moretti (2013) studied a mixed-frequency model for daily forecasts of euro area inflation. Their model combined a monthly index of core inflation with daily data from financial markets; estimates are carried out with the Mixed Data Sampling (MIDAS) regression approach. Thus, the forecasting ability of the model in real time is compared with that of standard VARs and of daily quotes of economic derivatives on euro area inflation. In sum, they find that "the inclusion of daily variables helps to reduce forecast errors with respect to models that consider only monthly variables. The mixed-frequency model also displays superior predictive performance with respect to forecasts solely based on economic derivatives"[19].

As we saw different there are various different approaches that help to reduce the inflation forecast errors. Each seemed to perform relatively well depending on the objective, the period and the country under consideration. In fact, Clark and Doh (2014) reviewed alternative models for the concept of trend inflation and compared the models on the basis of their accuracies in out-of-sample forecasting, both point and density. In sum, according to their results, they said that seem to be about equally accurate, and the relative accuracy is somewhat prone to instabilities over time"[20].

Neverthless, Rumler and Valderrama (2010) compared The New Keynesian Phillips Curve with time series models to forecast inflation. Therefore, they proposed a method of

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[18] Mikhail Chernov, Philippe Mueller (2012), "The term structure of inflation expectations" , Journal of Financial Economics, Nov.2012, Vol.106, Issue 2, p367-394

[19] Libero Monteforte, Gianluca Moretti (2013), "Real-Time Forecasts of Inflation: The Role of Financial Variables" , Journal of Forecasting, Jan 2013, Vol.32, Issue 1, p51-61. 11p.

[20] E. Todd Clark, Doh Taeyoung (2014), "Evaluating alternative models of trend inflation" , Internatiol Journal of Forecasting, July-Sept. 2014, Vol.30, Issue 3, p.426-448

forecasting inflation based on the present-value formulation of the hybrid New Keynesian Phillips Curve to evaluate the forecasting performance of this model using a Bayesian VAR, a conventional VAR and a simple autoregressive model. As a result, they concluded that “the New Keynesian Phillips Curve delivers relatively more accurate forecasts of inflation in Austria compared to the other models for longer forecast horizons (more than 3 months) while they are outperformed by the time series models only for the very short forecast horizon. This is consistent with the finding in the literature that structural models are able to outperform time series models only for longer horizons”[21].

Given the above evidence, then, we seek to measure the relative performance of a theoretical model along with two atheoretical models, one capturing the linearity and the other one capturing the non-linearity in the data, for foreasting Turkish inflation. In this way, our aim is to understand whether a theoretical approach is appropriate for forecasting the inflation of an emerging country like Turkey or a simple atheoretical model would yield a better result. To this end, we move in the next section to describe the estimation and forecasting study.

4) ESTIMATION AND FORECASTING STUDY

What follows is outlined (straightforwardly in parts) from Maliszewski (2003) (see also Yener (2006)). For estimating and forecasting inflation, I used equation of Maliszewski (2003) and compared its performance with AR (p,q) and TAR model.

Wojciech Maliszewski made his model to forecast the Georgian inflation rate. The theory in the study is built upon the perception that prices increase with increasing money supply and depreciating exchange rate, and decrease with growth (i.e. GDP growth) in equilibrium and over the long run. Consequently, Maliszewski formulation is given by

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

where all the variables are in logarithmic form, and p is the consumer price index, m is the money supply, e is the exchange rate and y is the GDP.

[21] Fabio Rumler, Maria Teresa Valderrama (2010), “Comparing the New Keynesian Phillips Curve with time series models to forecast inflation” , The North American Journal of Economics and Finance, August 2010, Vol.21, Issue 2, .126-144

We observe that the above equation depict the relationship between the price level and the relevant macro variables in emerging market economies. Therefore, the use of Maliszewski (2003)'s equation is intended to fill the gap which did not use these variables under structural models for predicting Turkish inflation.

4.1) Maliszewski's Equation for Inflation Forecast

Long-term price level (P) behavior determined when there is a balance between the aggregate demand (Y_D) and supply (Y_S) of goods and services. The aggregate demand for goods and services is, in turn, considered as a function of real money supply (M/P) and the real exchange rate (E/P). From this, the aggregate demand is given in the log linear form by

$$\mathbf{y_D = \alpha_1 (m - p) + \alpha_2 (e - p),} \qquad (1)$$

where the above equality is in log linear form and lower case letters are used to denote the variables. The dame form and notation is used throughout this section.

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

$$\mathbf{y = y_S = y_D} \qquad (2)$$

The above equality is obtained because Maliszewski (2003) assumed that the goods market is always in equilibrium.

Furthermore, following Maliszewski (2003) straightforwardly for the rest of this section, we write that the demand flow of foreign exchange is a function of real exchange rate and real income. Real income is at level with AS and is constant while real exchange tends to balance for foreign market currency. Money demand is supposed as a function of real income. Likewise, since real income is exogenous, real money balances tend to balance for the money market. If foreign exchange and money market are in equilibrium, the goods market is defined like equation (1) which is also in balance by application of the Walras law. If the market is in equilibrium, basic model defines 2 real variables (m-p and e-p) with one degree of freedom for determination of nominal variables (m,e and p). Fixing of the variables determines other two ones as providing a nominal power for the system. Empirically, if markets are in balance averagely, two special long run cointerating vectors probably occur between non-stationary nominal variables in equation (1) (treating y as exogenous). Moreover, money and foreign exchange markets may be permanently out of equilibrium (Adjustment is very slow or non-linear in equilibrium). Only, according to the assumption, goods market is always in equilibrium. In this situation, fixing one of the nominal variables does not provide a nominal power anymore to the system but fixing of two ones determines third one in the equation (1). Empirically, if two market are out of equilibrium, only one cointerating vector can be found in the data as answering to equality in the equation (1). Permanent pressure of exchange rate may be an example disequilibrium type before Russian crisis. This inequality had influenced money market in the foreign exchange market. Therefore, it would cause unbalanced of money market. While equilibrium had been finally restored in the foreign exchange and money markets, the permanent of disequilibrium and a probably non-linear adjustment process may obstruct finding two cointegrating vectors among the series. Supposing that only goods market is in equilibrium, substituting (2) into (1) and solving for p gives the equilibrium price level.

$$\boldsymbol{p = \alpha_1/(\alpha_{1+}\ \alpha_2)m + \alpha_2/(\alpha_{1+}\ \alpha_2)e - 1/(\alpha_{1+}\ \alpha_2)y} \qquad (3)$$

Equation (3) is similar with price equation which developed by Bruno (1993) who describes a long term relationship between prices, exchange rate, money and real income. Even if money and real income are out of equilibrium, it is suitable for estimation and testing in the cointegration framework. This equation shows us a neo-classical dilemma and y_S is fixed and equi-proportional changes in nominal variables leave the two real variables (m-p and e-p) unchanged. Testing for the neo-classical dilemma is equal to testing that the coefficients of money and exchange rate sum up to one.

4.2) Data

We used quarterly observations obtained from Organization for Economic Co-Operation and Development website[22] which covers a period between first quarter of 1999 and last quarter of 2013. We considered four variables; consumer pricing index (CPI), exchange rates (XRE), money supply (M) and gross domestic production (GDP) which are detailed below:

- XRE : End of period Exchange Rate (Liras per Dollar, buying rates)
- M2: Money in billion TL
- CPI: Consumer Price Index (2010=100)
- GDP: Real GDP (2010=100)

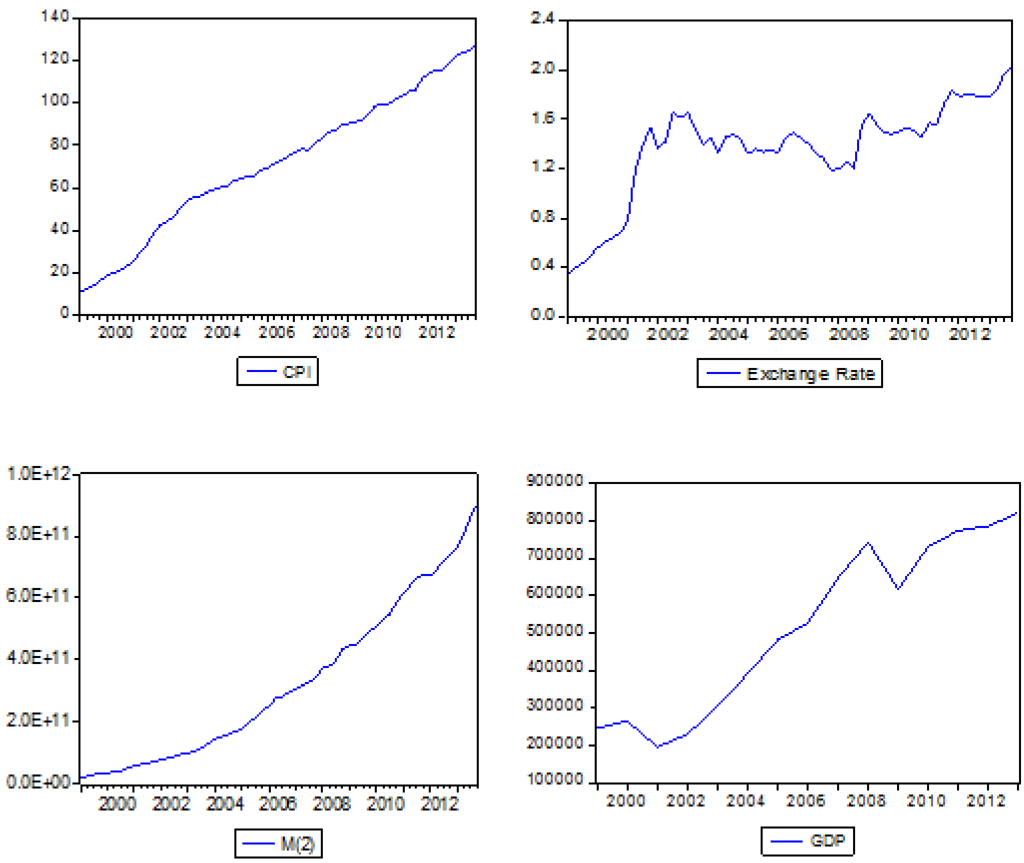


Figure 1: Plots of Time Series

[22] http://www.oecd.org/statistics/

Figure-1, illustrates the data used in the study. It is clear that the processes of all variables seem to follow an increasing trend. Therefore, they are non-stationary. Table-1 contains ADF (Augmented Dicky Fuller) test results of the series along with their first differences and logarithms.

Table 1: Unit Root Test Statistics

Type	CPI	M	XRE	GDP
Level	-1.0417 (0.7311)	6.9382 (1.0000)	-2.0912 (0.2489)	-0.3558 (0.8924)
First Difference	-2.3178 (0.1701)	-3.8680 (0.0040)	-6.0261 (0.0000)	-3.8746 (0.0137)
Logarithm	-3.5619 (0.0097)	-5.9878 (0.0000)	-4.2703 (0.0012)	-0.6822 (0.8203)

(Values in the parentheses show p-values.)

The results indicate that all series are I(1) except CPI which is I(2) process since we cannot reject unit root for both level and difference series for CPI. On the other hand, the log-series of the variables -which we feature in our analysis-, are all stationary except GDP.

4.3) Estimation Methodology and Results

4.3.1) Maliszewski's Equation

Maliszewski's Equation is an ordinary OLS model that aims to explain the behavior of inflation with macroeconomic variables rather than fitting in an ARIMA (Autoregressive Integrated Moving Average) type model. The model, however, includes an error correction variable which is especially used for dealing with non-stationary data. Nevertheless it is useful for stationary processes too. Here, we examine difference of log series which are stationary as seen in Table-2.

Table 2: Unit Root Test Results of Δ Log-Series

Dependent Variable	Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\Delta\ log(P_t)$	D(LOGCPI(-1))	-0.28361	0.088588	-3.20138	0.0023
$\Delta\ log(E_t)$	D(LOGXRE(-1))	-0.66539	0.202707	-3.28252	0.0019
$\Delta\ log(M_t)$	D(LOGM(-1))	-0.64408	0.139776	-4.60796	0.0000
$\Delta\ log(Y_t)$	D(LOGRGDP(-1))	-0.79581	0.162537	-4.89621	0.0000

Now, by following Maliszewski's Equation, we can write the model as

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

where,

$$ECM_{t-1} = P_{t-1} - \alpha_0 + \lambda_2 M_{t-1} + \gamma_2 E_{t-1} + \theta_2 Y_{t-1}$$

As seen above, the model aims to catch short term effects of macroeconomic variables rather than its does for longer periods. This may gain advantages compared to other methods in the context of adaptivity to new information which is not conceivable for ARIMA type models.

To perform the model we first obtain the residuals of the regression between log Pt and logEt, logMt, logYt. This procedure yields the ECM (Error Correction Model). After obtaining residuals, we regress Δlog Pt on the differences of logarithms of other macro variables along with ECM. Table-3 shows the results of the fitted model.

Table 3: Regression Results for Dependent Variable: Δ log(P_t)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$\Delta Ln(M_{t-1})$	0.352329	0.067963	5.184111	0
$\Delta Ln(P_{t-2})$	0.343366	0.087681	3.916085	0.0003
$\Delta Ln(M_{t-2})$	0.161257	0.071071	2.268956	0.0275
$\Delta Ln(E_{t-2})$	0.076639	0.042177	1.817075	0.0751
ECM_{t-1}	-0.14688	0.049559	-2.963744	0.0046
C	-0.010035	0.005611	-1.788438	0.0796
Adjusted R^2 : 0.739885				

We omitted the insignificant values except $\Delta Ln(E_{t-2})$ which is significant at 10% level. This is due to the fact that the model with $\Delta log(E_{t-2})$ has a higher Adjusted R^2 than the model without it. The results show that GDP has no effect in explaining inflation. On the other hand, second order lag of $\Delta log(P_t)$ is significant while the first lag of $\Delta log(P_t)$ is insignificant. Furthermore, we also observe that the first and second order lags of Monetary Supply and the first order lag of ECM are significant.

To check if the model satisfies the OLS (Ordinary Least Squares) assumptions we applied several tests (further details are provided in Appendix C) which are summarized in Figure-4 and Table-5. These tests are performed to confirm whether our structural model may be used for a forecast study. Before proceeding with these findings we provide further explanation of our model.

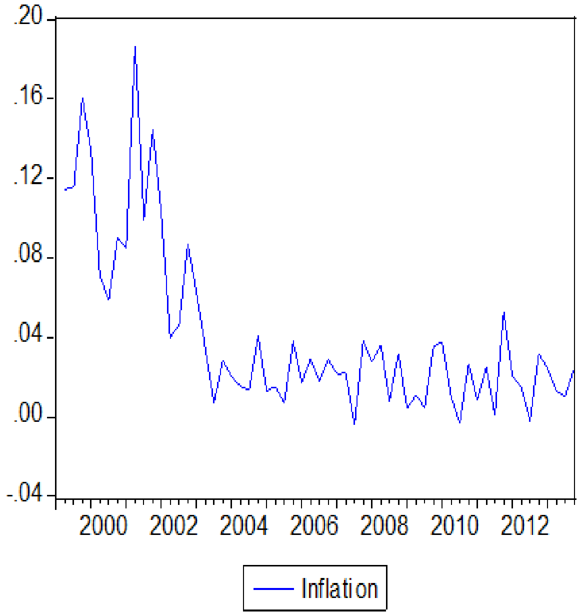
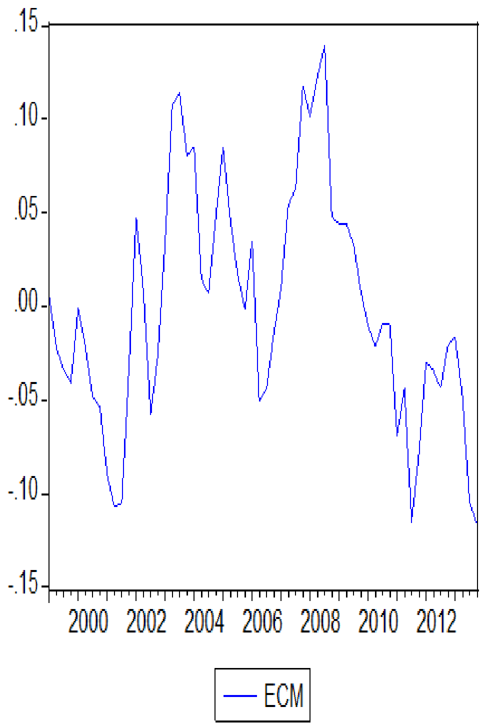


Figure 2: Quarterly Path of Turkish Inflation

First, we observe the significant coefficient of the lagged inflation showing the impact of previous inflation values on current values. Because its coefficient is the second largest value, we can understand that inflation inertia exists in Turkey because inflationary expectations played an important role for Turkish inflation. Therefore, a percentage point increase in ΔP_{t-2} increases inflation by around 0.34 percentage points.

Besides, the negative coefficient of the error correcting model shows effect of the long run adjustments to Turkish inflation. So, when inflation diverge from its long run way, it adjusts to its fair value with a speed equivalent to the coefficient value of ECM. In other words, if inflation is higher than the long run rate, the model, given its negative coefficient, adjusts inflation to the expected long run value of ECM's coefficient.



Furthermore, we need to check whether the price level is cointegrated with the macro variables considered for the theoretical model. If the residuals are I(0), we can say that the variables are cointegrated. The Figure-3 shows the path of the residuals obtained from the regression described above. Therefore, it shows that the residuals follow a stationary trend. The test statistic results below also shows that the residuals are I(0), because the probability value represent the stationary behavior of residuals. Therefore, we reject the null hypothesis of non-stationarity. Thus, we can say that price level is cointegrated with exchange rates, output, and money.

Figure 3: Plot of Errors

Null Hypothesis: ECM has a unit root			
Exogenous: None			
Lag Length: 0 (Fixed)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.120374	0.0337
Test critical values:	1% level	-2.604746	
	5% level	-1.946447	
	10% level	-1.613238	

Once the cointegration among $\Delta Ln(P_t)$, $\Delta Ln(E_t)$, $\Delta Ln(M_t)$, and $\Delta Ln(Y_t)$ is established, it remains for commenting on the long run feature between the variables. The results 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 look at the appendix B for more details.)

Table 4: The Effects of Variables

Dependent Variable: $\Delta Ln(P_t)$	
Variable	**Coefficient**
Intercept	-6.877173
$\Delta Ln(E_t)$	0.539701
$\Delta Ln(M_t)$	0.415474
$\Delta Ln(Y_t)$	0.558099

The results above show that the price level is positively related to the growth in money, output and exchange rate. This result is compatible with the theoretical suggestion, as the growth in output and money and a depreciation of the currency causes an increase in inflation in the long run. Therefore, 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 0.53, 0.41 and 0.55 percentage points.

Next, we proceed to see if the model is stable enough to use for a forecast model.

Table 5: Test Results for Reliability of Maliszewski Model

Test	Statistic Value	P-value	Null Hypothesis (H_0)	Reject / Not Reject H_0
Jarque-Bera	2.527764	0.282555	Normality	Not Reject
LM Test	0.414244	0.7299	No serial correlation	Not Reject
White Heteroskedasticity Test*	0.682983	0.6384	Homoscedastic	Not Reject
Chow Breakpoint Test (2003 Q2)	6.236138	0.0001	No Structural Change	Reject
RESET Test	22.69919	0.0000	Correct Specification	Reject
ARCH Test	0.812372	0.3714	No ARCH Effect	Not Reject

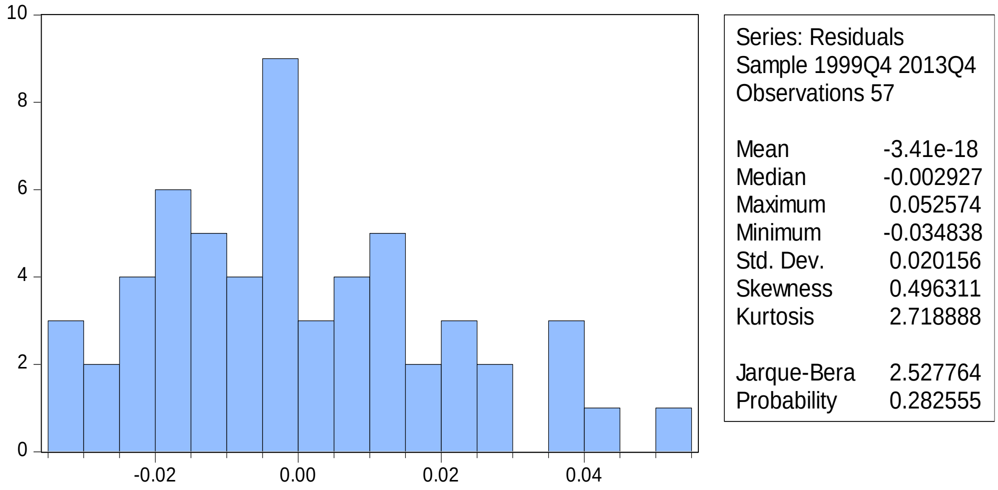


Figure 4: Histogram for Normality

By Jarque-Bera test statistics, we cannot reject the normality of residuals. On the other hand, we cannot reject homoscedasticity according to Breusch-Pagan-Godfrey test statistics, and from LM test results we do not see serial correlation between residuals. Besides ARCH test supports these results; thus, we cannot reject that the residuals are distributed IID N (0,1) and that there is neither serial correlation nor heteroscedasticity in the residuals. As a result, constructing the model on the basis of the normally distributed homoscedastic errors is good enough for a forecast study.

However, RESET test results are not desirable since we reject the null hypothesis that the explanatory variables are correctly specified. Yet, in grand scheme of the results the model is reliable.

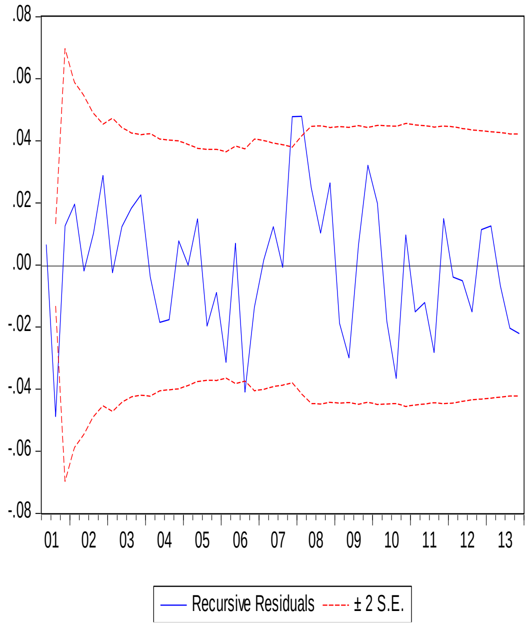
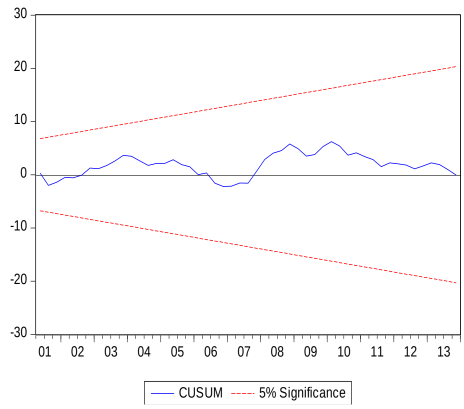


Figure-5 shows a plot of the recursive residuals about the zero line. Plus and minus two standard errors are also shown as the dotted lines at each point. Residuals outside the standard error bands show instability in the parameters of the equation. Therefore, around 2001, 2007 and 2008 parameters of the equation seem to become slightly (2008 is the heaviest) unstable due to the financial crisis. This instability is also determined with the structural break point identified with the chow breakpoint tests above.

Figure 5: Plot of Recursive Residuals

Figure-6 and Figure-7 plot the cumulative sum together with the 5% critical lines. Therefore, we try to find parameter instability if the cumulative sum tend to go outside the area between the two critical lines. According to the figures, we can say that our parameters are stable since the line stays in between the 5% critical lines. Therefore, we can obtain good forecast results using our regression model.



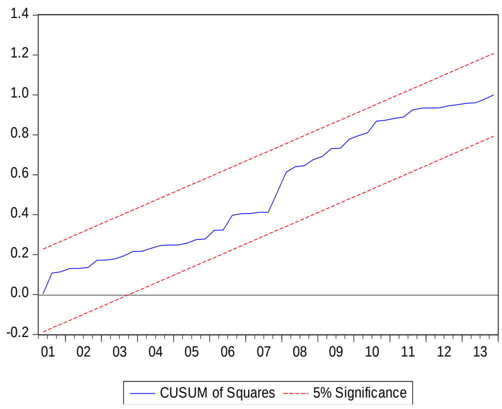


Figure 6: Plot of Cumulative Sum **Figure 7: Plot of Cumulative Sum of Squares**

Figure-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 2006, 2008 and 2011 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 Figure-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.

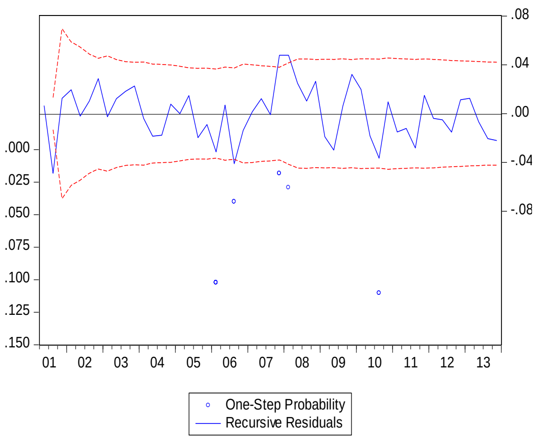


Figure 8: One-Step Probabilities

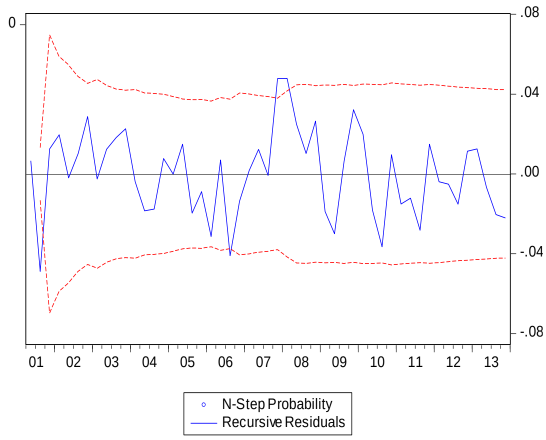


Figure 9: N-Step Probabilities

Consequently, looking at the recursive coefficient below figures, we can say that all variables have significant variances in the short run. Generally, the recursive coefficient graphs of the variables in the model have sudden movements in parts but stabilize at new level. However, the variables seem to stabilize as more data over the sample period are added in the medium and the long run. The coefficients of ΔE_t and ΔM_t, seem to follow a more stable path when the model uses more data. Nevertheless, the coefficients of the first lag ECM become negative given the application of the same procedure. There is only instability on intercept and it is significantly different than zero. In addition, since a lot of data is used, the coefficient of the first lag of inflation becomes positive.

Even though we observe variations in the recursive coefficients figures, they usually appear only one time and they are relatively small. Therefore, we can say that our model can be compatible to forecast inflation considering the previous tests.

Figure 10: Recursive Coefficients

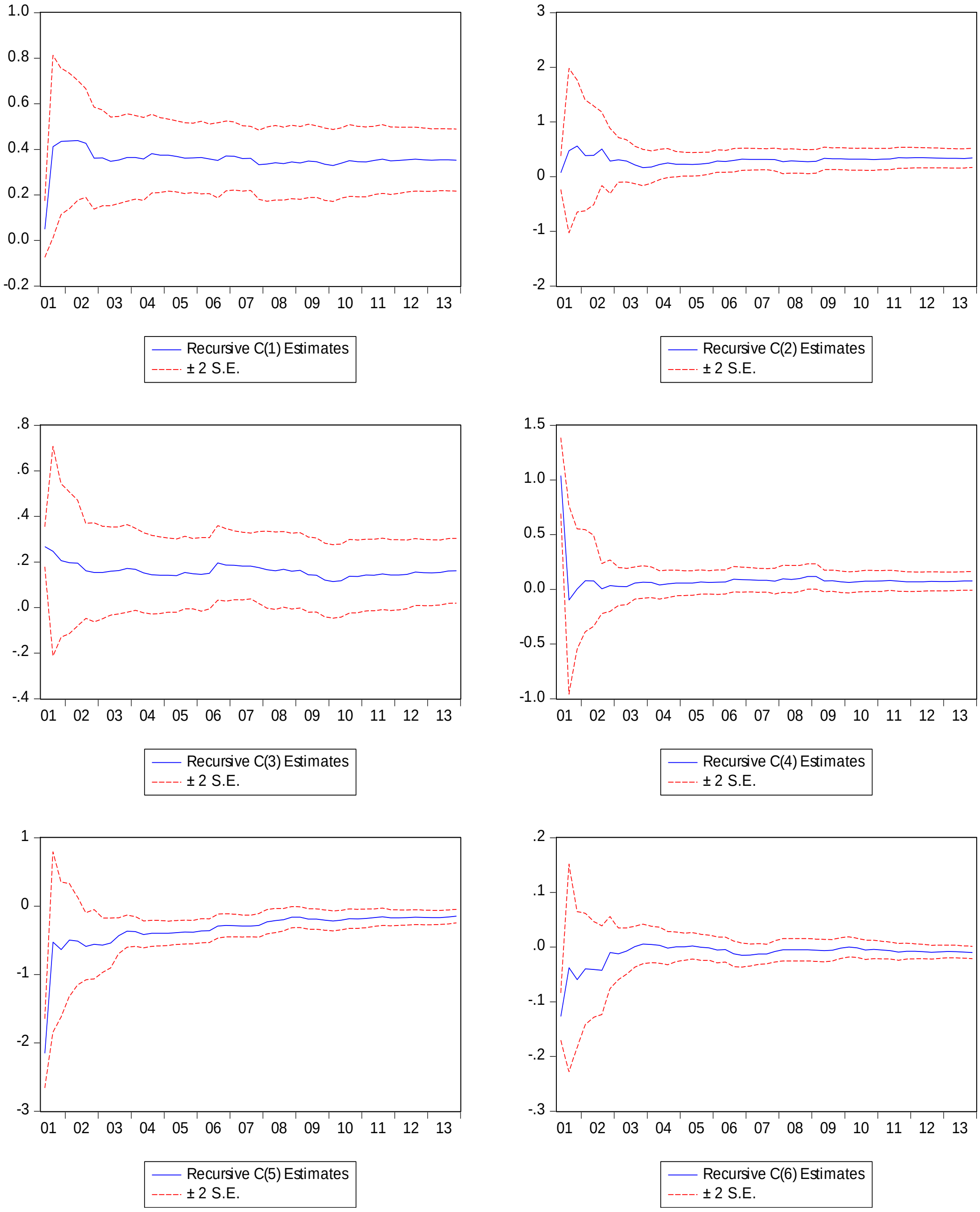


Table 6: Explanation of Variables

Variable	Coefficient Indicator
C(1)	$\Delta\log(M_{t-1})$
C(2)	$\Delta\log(Y_{t-2})$
C(3)	$\Delta\log(M_{t-2})$
C(4)	$\Delta\log(E_{t-2})$
C(5)	ECM_{t-1}
C(6)	Coefficient

4.3.2) ARMA(p,q) Model

As a second model, we consider ARMA(p,q) model which is a common approach in the forecasting literature. Rather than using plain vanilla, various of its modulations are used in forecasting, however using it in its simples form gives insight for a behavior of a stationary process and helps to use it as a benchmark when comparing it with different models.

ARMA(p,q) process is a combination of autoregressive process with order of p and moving average process in order of q. Its general form is;

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t$$

Here p and q are lag orders to detect the effect of past noise or price levels on today's price. In this sense, autocorrelations (AC) and partial autocorrelations (PAC) are often referred to give insight for the lag orders. To this end we will first present the correlogram of log P_t

Date: 12/30/14 Time: 22:15
Sample: 1999Q1 2013Q4
Included observations: 59

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.714	0.714	31.643	0.000
		2	0.640	0.266	57.516	0.000
		3	0.482	-0.094	72.475	0.000
		4	0.489	0.197	88.092	0.000
		5	0.453	0.098	101.79	0.000
		6	0.504	0.166	119.05	0.000
		7	0.437	-0.050	132.28	0.000
		8	0.461	0.104	147.30	0.000
		9	0.217	-0.441	150.69	0.000
		10	0.160	-0.085	152.58	0.000
		11	0.096	0.096	153.28	0.000
		12	0.138	0.010	154.74	0.000
		13	0.045	-0.234	154.91	0.000
		14	0.038	-0.019	155.02	0.000
		15	-0.058	0.030	155.30	0.000
		16	-0.021	0.116	155.34	0.000
		17	-0.103	0.082	156.24	0.000
		18	-0.063	0.026	156.60	0.000
		19	-0.093	-0.076	157.37	0.000
		20	-0.025	0.129	157.43	0.000
		21	-0.086	0.096	158.13	0.000
		22	-0.089	-0.145	158.90	0.000
		23	-0.125	-0.075	160.45	0.000
		24	-0.061	0.020	160.83	0.000

Figure 11: Correlogram of Log P_t

Figure-11, implies positive autocorrelation in high order with significant partial autocorrelation. This indicates that impact of early levels is long for a while and the impact of early noises is not ceasing rapidly. Hence, we apply ARMA(3,2) for p,q ϵ {1,2,3}.

4.3.3) ARMA (3,2) Model

Table 7: ARMA(3,2) Results on Δ log(P_t)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLCPI(-1)	0.3457	0.1295	2.6684	0.0102
DLCPI(-2)	0.9342	0.0229	40.8598	0.0000
DLCPI(-3)	-0.3870	0.1155	-3.3516	0.0015
C	0.0018	0.0008	2.2151	0.0312
MA(2)	-0.9995	0.0492	-20.3198	0.0000
Adjusted R^2 : 0.673279				

Here, we reject null hypothesis that coefficients are equal to zero at 5% significance level and model has a relatively high Adjusted R^2. Results implies that in Turkish case, inflation is highly correlated with the annual realizations of second order lag of moving average process.

To check the reliability of the results we will check if the model satisfies the OLS assumptions. At first look to correlogram on residuals[23], we can say that there is no AC or PAC 5% significance level. But, we need further analysis to test the reliability of the model. Findings are summarized results in Table-8.

[23] Please, see Appendix D for Figure 25.

Table 8: Test Results for Reliability of ARMA(3,2)

Test	Statistic Value	P-value	Null Hypothesis (H_0)	Reject / Not Reject H_0
Jarque-Bera	75.05019	0.00000	Normality	Reject
LM Test	0.74695	0.47910	No serial correlation	Not Reject
White Heteroskedasticity Test	10.45980	0.00000	Homoscedastic	Not Reject
Chow Breakpoint Test (2003 Q1)	5.04404	0.00090	No Structural Change	Reject
RESET Test	32.85478	0.00000	Correct Specification	Reject
ARCH Test	0.18307	0.67050	No ARCH Effect	Not Reject

LM test results also confirm that there is no serial autocorrelation in the residuals. Moreover, neither White Heteroskedasticity Test nor ARCH test rejects homoscedasticity, thus the model satisfies the OLS assumptions.

On the other hand, according to Chow Breakpoint Test, there is a structural break in the first quarter of 2003 which is consistent with consequences of new economic policies of the new government elected after 2002.

Lastly, normality of residuals is not supported by Jarque-Bera test. This assumption is not easily satisfied, but often supported with some other tests. However RESET test results does not support the specification either. We skip the OLS type structural break tests on residuals since they are not supported for MA processes in E-views statistics package.

4.3.4) AR (2) Model

In this subsection we will also check how AR model explains the inflation data. After several trials, we fit AR(2) model to difference of the *log* P_t series. The results are presented in Table-9.

Table 9: AR(2) Model on Δ log(P_t)

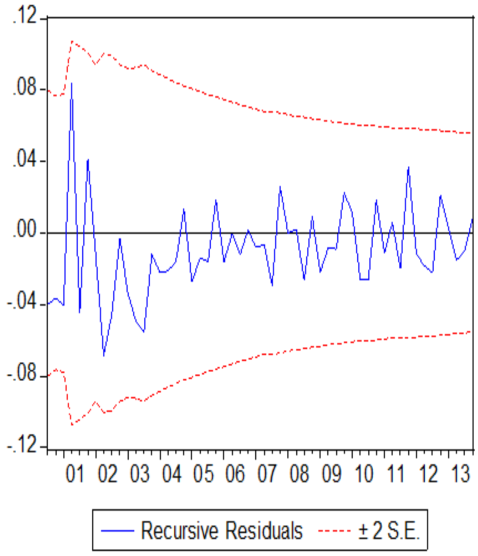
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006801	0.005315	1.279552	0.2062
DLCPI(-1)	0.461097	0.127851	3.60653	0.0007
DLCPI(-2)	0.318088	0.125217	2.540289	0.014
Adjusted R^2 : 0.552679				

Results are parallel with those of ARMA(3,2) except that the third lag is omitted because of its insignificance. In contrast, Table-9 shows that both the first and second order lags of inflation have positive effect on today's inflation as in ARMA(3,2). However neither AIC, nor Adjusted R^2 is greater than the former model. On the other hand, the reliability of AR(2) draws similar picture compared to ARMA(3,2). Correlogram of the residuals[24] and LM test verifies that there is no serial autocorrelation in the residuals. White Heteroskedasticity Test and ARCH test also implies that the residuals are homoscedastic. Yet, RESET test is higher as well as it is below the significance level. Considering Jarque-Bera Normality Test on residuals, the model does not satisfy the normality assumption either.

Table 10: Test Results for Reliability of AR(2)

Test	Statistic Value	P-value	Null Hypothesis (H_0)	Reject / Not Reject H_0
Jarque-Bera	52.65655	0	Normality	Reject
LM Test	1.626681	0.200681	No serial correlation	Not Reject
White Heteroskedasticity Test	3.411676	0.014965	Homoscedastic	Not Reject
Chow Breakpoint Test (2003 Q2)	6.230316	0.001094	No Structural Change	Reject
RESET Test	5.345687	0.007739	Correct Specification	Reject
ARCH Test	0.14395	0.705873	No ARCH Effect	Not Reject

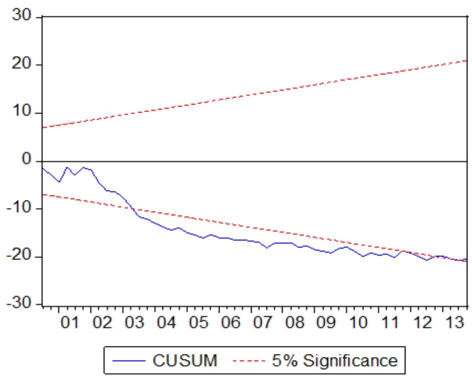
[24] Please, see Appendix D for Figure 25.



On the other hand, the plot of recursive residuals for AR(2) model of inflation shows that the parameters became unstable around 2001, 2002, and 2011 (2001 is the heaviest). In addition, the significance bands shown with dotted lines are bigger than those of the Maliszewski's Equation. As you see them on the graph, they follow an unstable model path until 2001 and become more stable after this period.

Figure 12: Plot of Recursive Residuals

The figures below plot the cumulative sum together with the 5% critical lines. According to the Figure-13, we can say that the parameters of AR(2) model are not stable since the line stays in between the 5% critical lines. In addition, a detailed analysis with the cumulative sum of squares shows that the parameters become unstable between 2002 and 2008 since they stay fairly outside the 5% significance band. Therefore, there is a possibility that AR(2) model may not yield good forecast results.



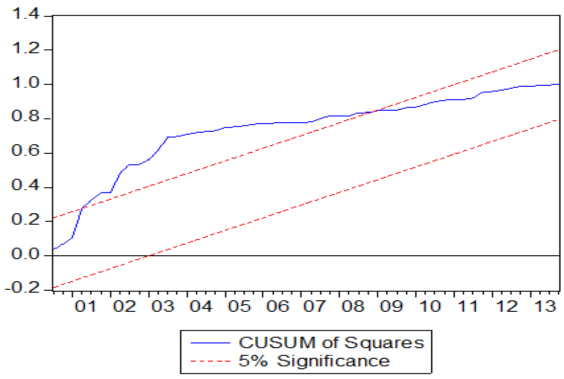


Figure 13: Cumulative Sum of AR(2) **Figure 14: Cumulative Sum of Squares of AR(2)**

The One-Step probability test results show that the most successful periods for the AR(2) model estimations are around year 2001 and 2003 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 2001 and 2003.

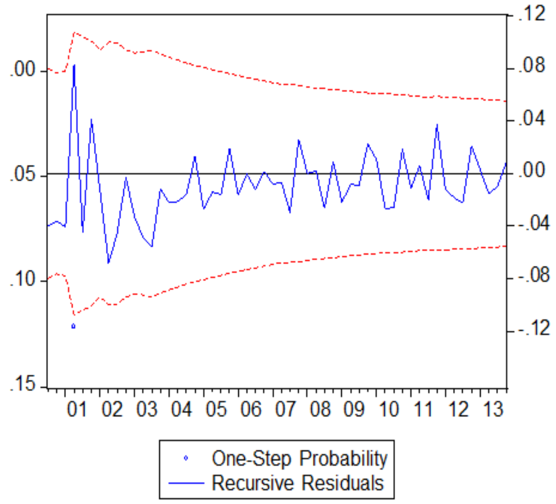


Figure 15: One Step Probability Plot of AR(2)

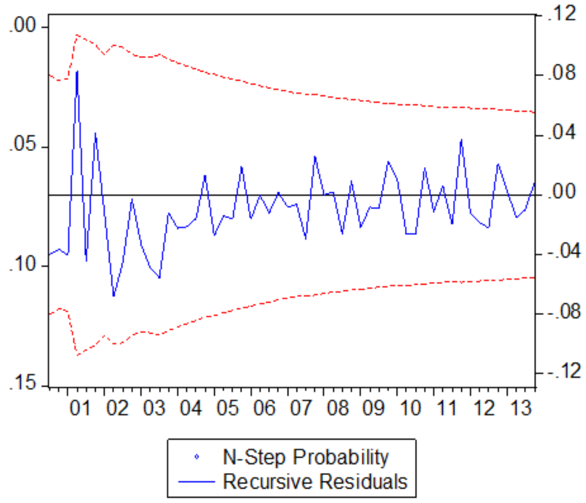


Figure 16: N-Step Probability Plot of AR(2)

Eventually, according to the recursive coefficient graphs, all variables have significant variances in the short run. However, they seem to stabilize in the medium-run but since more data are added in the period, they move to a new level in the long run. Nevertheless, the variability is very high in the coefficients in the short run since there are significant structural breaks in the economy during those periods (as confirmed in the above tests).

Figure 17: Recursive Coeffcients Plot of AR(2)

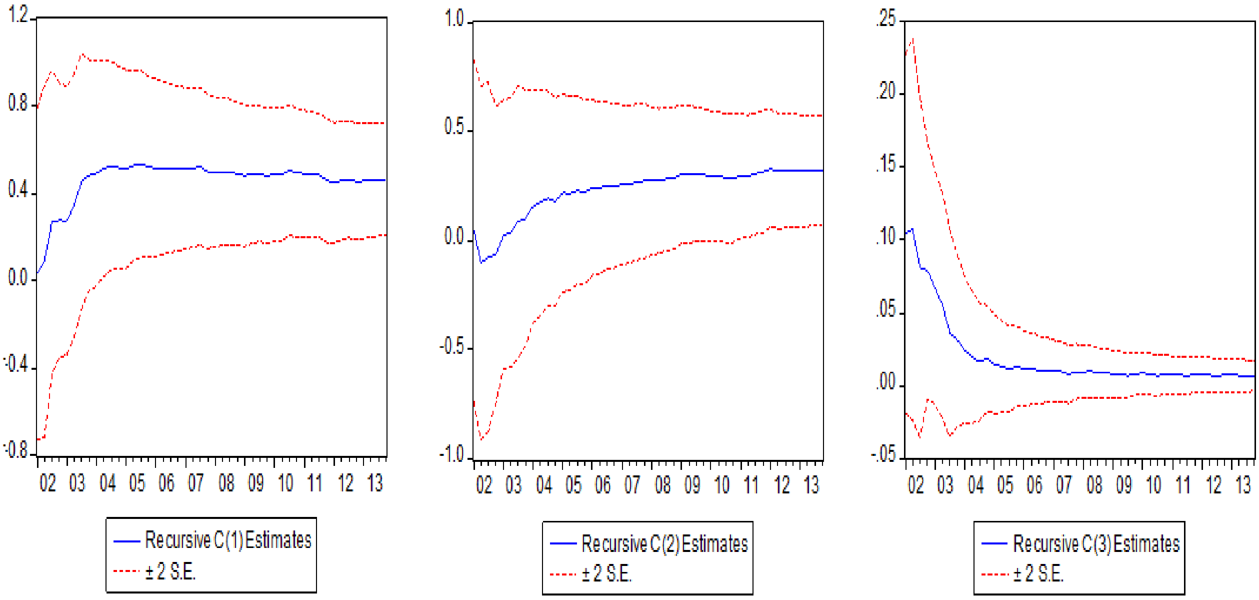


Table 11: Description of Coefficients

Variable	Coefficient Indicator
C(1)	C
C(2)	DLCPI(-1)
C(3)	DLCPI(-2)

4.3.5) TAR Model

Considering policy changes on inflation in the last 15 years, meaningful structural changes can be observed in the series; hence, a regime switching model may help better to clarify the movements of inflation. Therefore, we will apply another model, Threshold Autoregressive Model (TAR), to catch structural changes in depreciation, crisis or periods. The basic motive behind TAR model is to fit a line for the each case when the dependent variable rises above or falls below a threshold which is determined either manually or based on an information criterion such as AIC (Akaike Information Criterion). The general formula of TAR model is;

$$\Delta Log(P_t) = \begin{cases} c_l + \sum_1^p \beta_p^l \Delta \log(P_{t-p}) + \varepsilon_t & if\ \Delta \log P_{t-d} \leq th, \\ c_u + \sum_1^p \beta_p^l \Delta \log(P_{t-p}) + \varepsilon_t & if\ \Delta \log P_{t-d} > th \end{cases}$$

where p is the order of model and d is the lag-order determines the threshold. Table-12 shows the statistical results of TAR model performed on $\Delta \log P_t$[25]

Table 12: TAR(2) Results for Δ log(Pt)

	Estimate	Std. Error	t-Statistic	Prob.
c_l	0.0267	0.0038	7.0826	0
β_1^l	-0.3666	0.1702	-2.01542	0.0376
c_u	0.035	0.0265	1.3207	0.2064
β_1^u	0.5327	0.2599	2.0495	0.0583

The model with minimum AIC is attained with threshold equal to 0.03851. Thus, under the statistical results we can write TAR(2) model as;

$$\Delta Log(P_t) = \begin{cases} 0.0267 - 0.3666\, \Delta \log(P_{t-1}) & if\ \Delta \log P_{t-1} \leq 0.03851\, (\%3.85) \\ 0.035 + 0.5327\, \Delta \log(P_{t-1}) & if\ \Delta \log P_{t-1} > 0.03851\, (\%3.85) \end{cases}$$

[25] Insignificant values are omitted

The results shows that TAR(2) model catches the change in policy of economics in 2003 which can be seen clearly in Figure-18. Here, we see that the threshold detected via the minimum AIC fits well in the difference of the *log* P_t series. Besides, the above equation indicates that the change between regimes is not only different, but also is contrary when we keep in sight the change of coefficients. That is, whenever we are in the upper regime, due to one period inflation inertia, the inflation rate in Turkey tends to increase. On the other hand, we observe from the lower regime that the rate of inflation in Turkey tends to decline thanks to negative one period inflation inertia. Moreover note that the second lags are both omitted because of their insignificance. This implies the ineffectiveness of earlier inflation for more than one quarter on upcoming realizations.

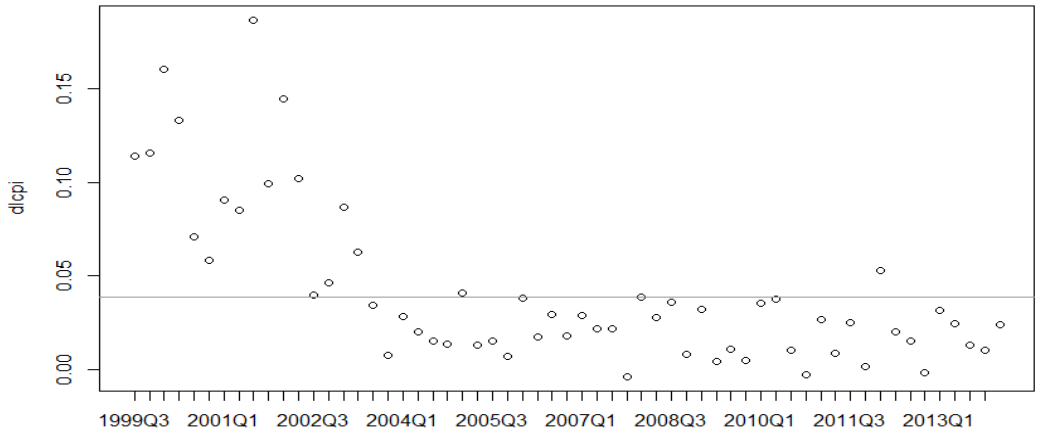


Figure 18: Δ log P_t Plot with Threshold

Next, to check if TAR model satisfies the OLS assumptions we performed tests on residuals which are shown in Table-13. LM Test results imply that the residuals are not serially correlated, which goes parallel with the correlogram of the residuals (Please, See Figure-26 in Appendix E). On the other hand, ARCH test confirms that the series are not correlated, however, the model does not prevent heteroskedasticity in the residuals according to Breusch-Pagan-Godfrey (BPG) test results. This is not a desired result, yet, it is significant at 1% level, besides when we take BPG along with ARCH results the statistics could be admissible. Furthermore, RESET Test statistics implies the specifications of the variables are correct. Lastly, the normality of the residuals are not supported by Jarque-Bera test. Nevertheless, it is not a detrimental result considering the forecasting literature.

Table 13: The results of Reliability of TAR (2)

Test	Statistic Value	P-value	Null Hypothesis (H_0)	Reject / Not Reject H_0
Jarque-Bera	61.8927	0.0000	Normality	Reject
LM Test	3.4233	0.1806	No serial correlation	Not Reject
Breusch-Pagan-Godfrey Test	12.119	0.0165	Homoscedastic	Reject
RESET Test	0.0000	1.0000	Correct Specification	Not Reject
ARCH Test	0.0103	0.919	No ARCH Effect	Not Reject

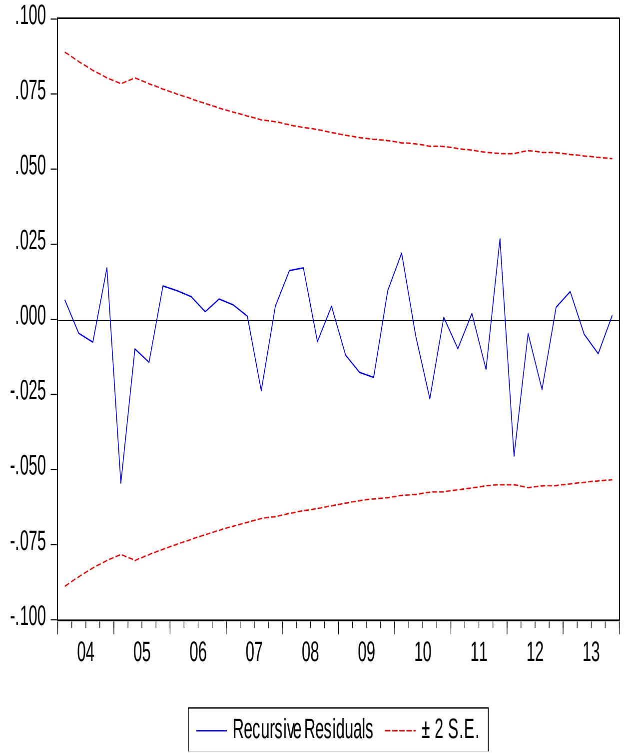
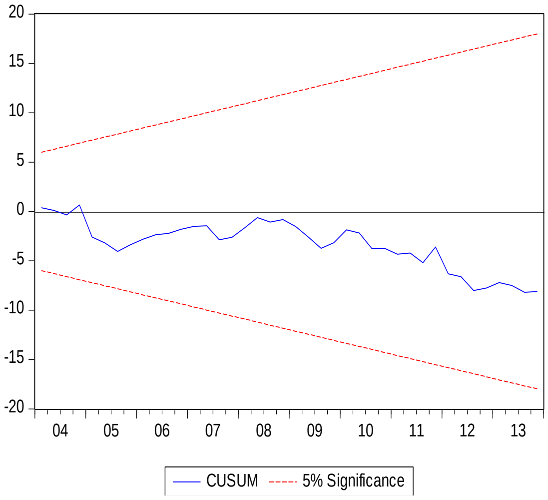


Figure 19: Plot of Recursive Residuals – TAR (2)

Furthermore, the figure of recursive residuals shows that the TAR model had a stable performance along the observation period. This situation may be due to the fact that TAR model gets hold of the non-linear behavior or structural breaks of inflation. However, we should note that the bands depicted with dotted lines are wider than those in the graph of recursive residuals for Maliszewski's Equation. For this reason, the stability of TAR model is verified at a higher critical value. Nevertheless, since we move along the graph (to the right hand side), we obtain a more stable pattern for the model.

As we see, the figures below plot the cumulative sum together with the 5% critical lines for the TAR model. Therefore, 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 that the parameters are stable.



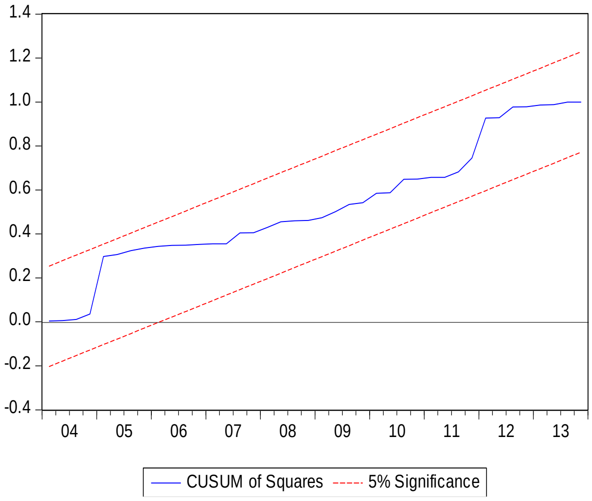
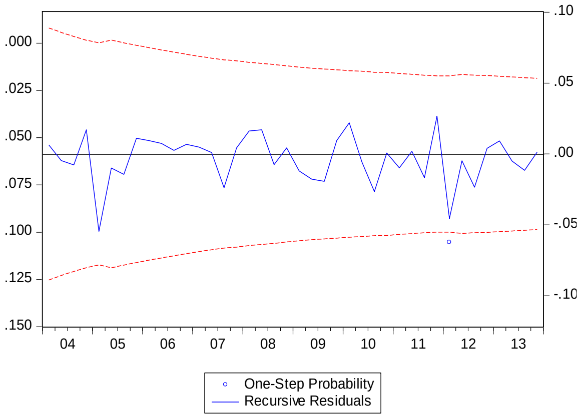


Figure 20: Cumulative Sum of TAR(2) **Figure 21: Cumulative Sum of Squares TAR(2)**

Figure-22 and Figure-23 below show The One-Step and N-Step Probability tests results for TAR model. Looking at the result of one-step probability, we may say that the least successful period is in 2012, since the point below the recursive residual corresponds to this year. However, the N-step probability tests show the most applicable cases by carrying a multiple Chow Forecast tests for forecasting. Naturally, we see that a non-linear determination properly performs with the data, because it gets hold of the structural breaks in the economy.



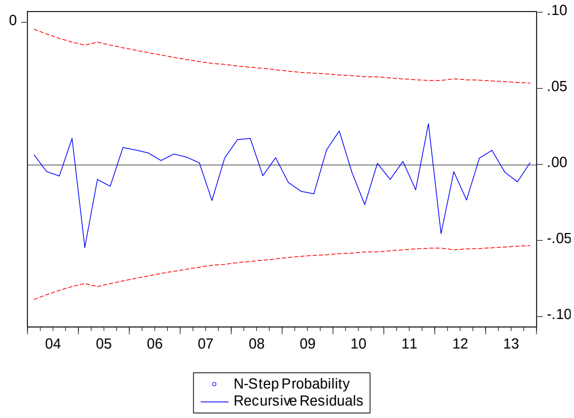


Figure 22: One Step Probability Plot of TAR(2) **Figure 23: N Step Probability Plot of TAR(2)**

Eventually, according to the recursive coefficient graphs, all variables have significant variances in the short run. However, they seem to stabilize in the medium-run, since more data are added in the period they move to a new level in the long run. Nevertheless, the variability is very high in the coefficients in the short run since there are significant structural breaks in the economy during those periods (as confirmed in the above tests).

Figure 24: Recursive Coefficients Plot of TAR(2)

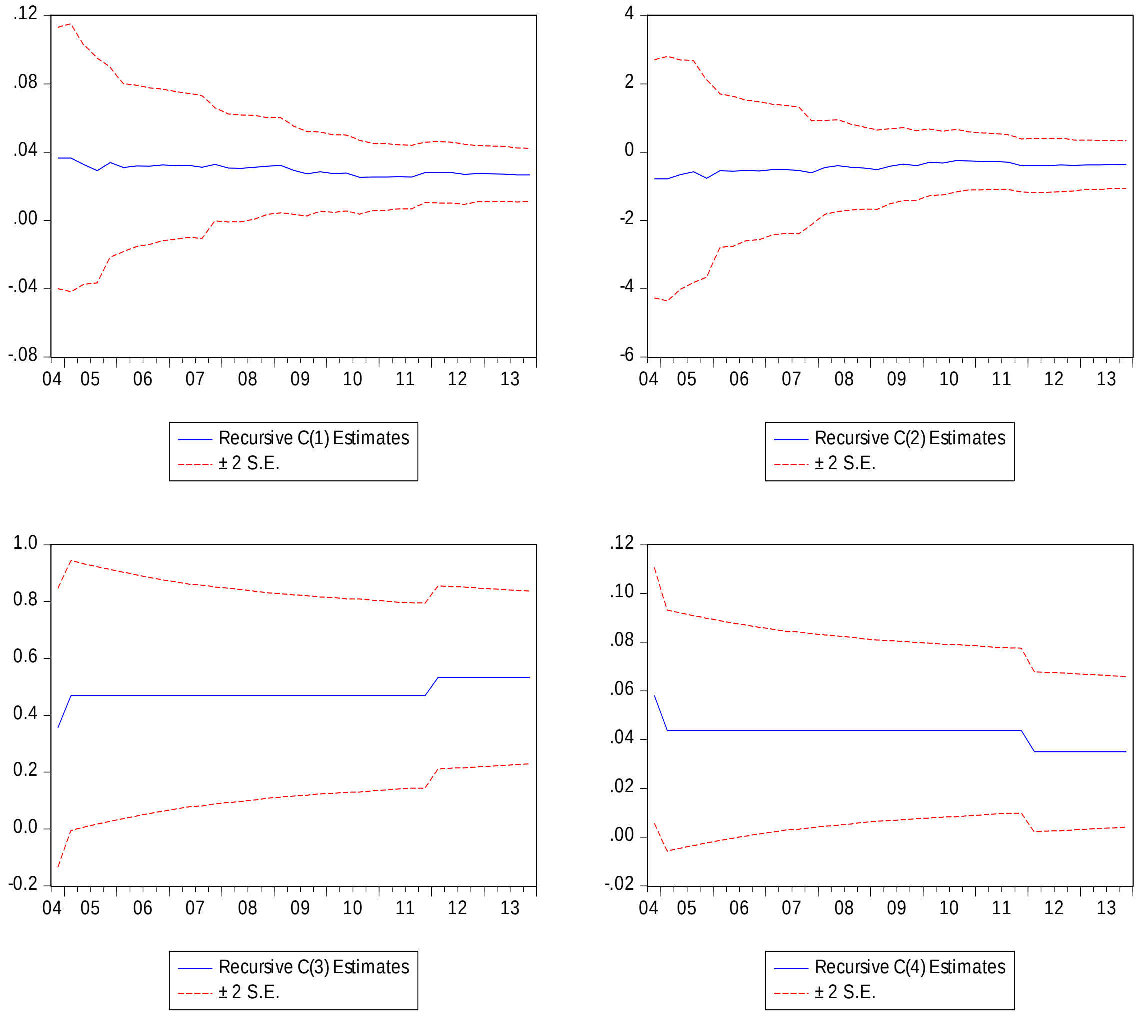


Table 14: Description of Coefficients

Variable	Coefficient Indicator
C(1)	c_l
C(2)	β_1
C(3)	c_u
C(4)	β_u

4.3.6) Forecast Results

The pseudo out-of-sample forecasts are conducted based on dynamic rolling regression starting with 1999Q1-2013Q4. The forecast period is 2013Q1 and 2013Q4. Therefore, the forecast horizon is one year. The reason for selecting 2013 is that the period was one of the most stable periods in the history of Turkish economy. In addition to this reason, because economic improvement has been provided since the period of between 2003 and 2004. Therefore, recent years have a stable economic structure.

Afterwards, I compare the root mean square error (RMSE), mean absolute error (MAE) and Theil's inequality coefficient. RMSE penalizes the models with large prediction errors. Therefore, it has a good comparison advantage. However, if there is a steady trend, thus MAE may be used to select the best performing model. Likewise, Theil's inequality coefficient takes values between 0 and 1, with zero being the perfect forecast prediction.

The table below shows the summary of the results. More results are provided in Appendix F.

Table 15: The Summary of The Results

Model	RMSE	MAE	Theil’s Inequality Coefficient
AR(2)	0.010117	0.00922	0.24734
TAR Model	0.007746	0.00667	0.200028
Maliszewski’s Equation	0.015973	0.01475	0.333746

According to the Theil's Inequality coefficients, we see that AR (2) and TAR models have good forecasting performances since the Theil's Inequality Coefficients are closer to 0 than those of Maliszewski’s model. However, TAR model outperformed both AR(2) and Maliszewski’s Equation. Therefore, it is the best performing model. Eventually, TAR Model performs better than AR(2) and Maliszewski’s Equation.

5) CONCLUSION

The money, output and exchange rate series are found to be I(1) and are cointegrated. Therefore, the price level is positively related to the growth in exchange rate, money and output in the long run. This conclusion is suitable with the theoretical suggestion, as the growth in money, output and depreciation causes an increase in inflation in the long run. Therefore, Turkish inflation is positively affected by the contemporaneous depreciation and monetary and output growths ($\Delta Ln(E_t)$, $\Delta Ln(M_{t,})$, $\Delta Ln(Y_{t,})$) in the short run.

Moreover, the presence of the lags show the significance of adjustment lags in Turkish economy. The fact that both money and exchange rate growth have lags shows that Turkish inflation is prone to the impacts of earlier policies. Also, the impact of the money is higher than the impact of depreciation. Therefore, this situation shows us decreasing exposure of Turkish economy to international effect. In addition, the presence of inflation lag confirms the inflation inertia in Turkey. Moreover, the negative coefficients of the contemporaneous monetary growths in the Maliszewski's Equation suggest the expansionary policy have not been followed anymore by Turkey throughout the years given the fact that Turkey is an emerging market.

The finding of inflation inertia by the Maliszewski'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 TAR model 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. Furthermore, CUSUM tests show that the performance of the model is reliable, since it does not stay within the 5% significance band. In addition, the results of diagnostics tests show that the results of the TAR model may be perceived as reliable. This is also well confirmed by the fact that TAR models perform better than both AR(2) and Maliszewski's Equation. Comparison with AR(2) model shows that TAR model perform better than AR(2), the mostly utilized benchmark model for forecasting inflation.

In addition, Maliszewski's Equation has the worst forecast performance among them, although it is built for developing countries. In summary, TAR Model and AR(2) Model, which are atheoretical models, show better than Maliszewski's Equation which is a theoretical model.

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7) APPENDICES

7.1) Appendix A: ADF Tests on Variables

Null Hypothesis: CPI has a unit root
Exogenous: Constant
Lag Length: 10 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.041733	0.7311
Test critical values:	1% level	-3.571310	
	5% level	-2.922449	
	10% level	-2.599224	

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

Null Hypothesis: D(CPI) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.317837	0.1701
Test critical values:	1% level	-3.555023	
	5% level	-2.915522	
	10% level	-2.595565	

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

Null Hypothesis: LOGCPI has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.561954	0.0097
Test critical values:	1% level	-3.550396	
	5% level	-2.913549	
	10% level	-2.594521	

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

Null Hypothesis: M has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		6.938224	1.0000
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

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

Null Hypothesis: D(M) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.868017	0.0040
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

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

Null Hypothesis: LOGM has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.987835	0.0000
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

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

Null Hypothesis: XRE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.091200	0.2489
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

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

Null Hypothesis: D(XRE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.026195	0.0000
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

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

Null Hypothesis: LOGXRE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.270324	0.0012
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

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

Null Hypothesis: GDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.355832	0.8924
Test critical values:	1% level	-4.004425	
	5% level	-3.098896	
	10% level	-2.690439	

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

Null Hypothesis: D(GDP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.874636	0.0137
Test critical values:	1% level	-4.057910	
	5% level	-3.119910	
	10% level	-2.701103	

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

Null Hypothesis: LOGGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=3)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.682248	0.8203
Test critical values:	1% level	-4.004425	
	5% level	-3.098896	
	10% level	-2.690439	

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

Null Hypothesis: D(LOGCPI) has a unit root
Exogenous: Constant
Lag Length: 0 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.201381	0.0249
Test critical values:	1% level	-3.548208	
	5% level	-2.912631	
	10% level	-2.594027	

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

Null Hypothesis: D(LOGXRE) has a unit root
Exogenous: Constant
Lag Length: 3 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.282523	0.0205
Test critical values:	1% level	-3.555023	
	5% level	-2.915522	
	10% level	-2.595565	

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

Null Hypothesis: D(LOGM) has a unit root
Exogenous: Constant
Lag Length: 1 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.607964	0.0004
Test critical values:	1% level	-3.550396	
	5% level	-2.913549	
	10% level	-2.594521	

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

Null Hypothesis: D(LOGRGDP) has a unit root
Exogenous: Constant
Lag Length: 1 (Fixed)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.896210	0.0002
Test critical values:	1% level	-3.550396	
	5% level	-2.913549	
	10% level	-2.594521	

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

7.2) Appendix B: Maliszewski's Equation Results

Dependent Variable: LOGCPI
Method: Least Squares
Date: 01/02/15 Time: 05:34
Sample: 1999Q1 2013Q4
Included observations: 60

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGM	0.415474	0.012994	31.97443	0.0000
LOGRGDP	0.558099	0.152899	3.650103	0.0006
LOGXRE	0.539701	0.034252	15.75681	0.0000
C	-6.877173	0.331989	-20.71506	0.0000

R-squared	0.990170	Mean dependent var	4.111538
Adjusted R-squared	0.989643	S.D. dependent var	0.637540
S.E. of regression	0.064881	Akaike info criterion	-2.568195
Sum squared resid	0.235732	Schwarz criterion	-2.428572
Log likelihood	81.04585	Hannan-Quinn criter.	-2.513581
F-statistic	1880.292	Durbin-Watson stat	0.376707
Prob(F-statistic)	0.000000		

Dependent Variable: DLCPI
Method: Least Squares
Date: 01/02/15 Time: 03:26
Sample (adjusted): 1999Q4 2013Q4
Included observations: 57 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLM(-1)	0.352329	0.067963	5.184111	0.0000
DLCPI(-2)	0.343366	0.087681	3.916085	0.0003
DLM(-2)	0.161257	0.071071	2.268956	0.0275
DLXRE(-2)	0.076639	0.042177	1.817075	0.0751
ERRLOG(-1)	-0.146880	0.049559	-2.963744	0.0046
C	-0.010035	0.005611	-1.788438	0.0796

R-squared	0.763110	Mean dependent var	0.039099
Adjusted R-squared	0.739885	S.D. dependent var	0.041413
S.E. of regression	0.021121	Akaike info criterion	-4.777799
Sum squared resid	0.022751	Schwarz criterion	-4.562741
Log likelihood	142.1673	Hannan-Quinn criter.	-4.694220
F-statistic	32.85796	Durbin-Watson stat	1.766566
Prob(F-statistic)	0.000000		

7.3) Appendix C: Diagnostic Test Results for the Maliszewski's Equation

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.414244	Prob. F(2,49)	0.7299
Obs*R-squared	0.000000	Prob. Chi-Square(2)	1.0000

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 01/02/15 Time: 03:59
Sample: 1999Q4 2013Q4
Included observations: 57
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLM(-1)	-0.023068	0.073934	-0.312006	NA
DLCPI(-2)	0.031656	0.101310	0.312463	0.7560
DLM(-2)	0.005467	0.072155	0.075764	0.9399
DLXRE(-2)	-0.006814	0.043368	-0.157110	0.8758
ERRLOG(-1)	0.001704	0.052613	0.032384	0.9743
C	-1.96E-05	0.005742	-0.003414	0.9973
RESID(-1)	0.115337	0.149124	0.773430	0.4430
RESID(-2)	-0.102245	0.180072	-0.567800	0.5728

S.E. of regression	0.021368	Akaike info criterion	-4.724390
Sum squared resid	0.022373	Schwarz criterion	-4.437646
Log likelihood	142.6451	Hannan-Quinn criter.	-4.612951
Durbin-Watson stat	1.982361		

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.682983	Prob. F(5,51)	0.6384
Obs*R-squared	3.577148	Prob. Chi-Square(5)	0.6117
Scaled explained SS	2.461189	Prob. Chi-Square(5)	0.7823

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/02/15 Time: 03:59
Sample: 1999Q4 2013Q4
Included observations: 57

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000205	0.000142	1.441011	0.1557
DLM(-1)	0.002713	0.001723	1.574064	0.1217
DLCPI(-2)	0.000340	0.002223	0.152720	0.8792
DLM(-2)	0.000200	0.001802	0.111131	0.9119
DLXRE(-2)	-0.000136	0.001070	-0.127551	0.8990
ERRLOG(-1)	-8.21E-05	0.001257	-0.065352	0.9481

R-squared	0.062757	Mean dependent var	0.000399
Adjusted R-squared	-0.029130	S.D. dependent var	0.000528
S.E. of regression	0.000536	Akaike info criterion	-12.12714
Sum squared resid	1.46E-05	Schwarz criterion	-11.91208
Log likelihood	351.6234	Hannan-Quinn criter.	-12.04356
F-statistic	0.682983	Durbin-Watson stat	2.280694
Prob(F-statistic)	0.638408		

Chow Breakpoint Test: 2003Q1
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 1999Q4 2013Q4

F-statistic	6.236138	Prob. F(6,45)	0.0001
Log likelihood ratio	34.49225	Prob. Chi-Square(6)	0.0000
Wald Statistic	37.41683	Prob. Chi-Square(6)	0.0000

Ramsey RESET Test
Equation: MLZEQ
Specification: DLCPI DLM(-1) DLCPI(-2) DLM(-2) DLXRE(-2) ERRLOG(-1) C
Omitted Variables: Squares of fitted values

	Value	df	Probability
t-statistic	4.764366	50	0.0000
F-statistic	22.69919	(1, 50)	0.0000
Likelihood ratio	21.33551	1	0.0000

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.007104	1	0.007104
Restricted SSR	0.022751	51	0.000446
Unrestricted SSR	0.015647	50	0.000313
Unrestricted SSR	0.015647	50	0.000313

LR test summary:

	Value	df
Restricted LogL	142.1673	51
Unrestricted LogL	152.8350	50

Unrestricted Test Equation:
Dependent Variable: DLCPI
Method: Least Squares
Date: 01/02/15 Time: 04:00
Sample: 1999Q4 2013Q4
Included observations: 57

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLM(-1)	-0.044593	0.100901	-0.441951	0.6604
DLCPI(-2)	0.031008	0.098446	0.314981	0.7541
DLM(-2)	-0.000513	0.068530	-0.007485	0.9941
DLXRE(-2)	-0.018480	0.040578	-0.455423	0.6508
ERRLOG(-1)	-0.048592	0.046353	-1.048299	0.2995
C	0.019397	0.007762	2.498888	0.0158
FITTED^2	7.776093	1.632136	4.764366	0.0000

R-squared	0.837075	Mean dependent var	0.039099
Adjusted R-squared	0.817524	S.D. dependent var	0.041413
S.E. of regression	0.017690	Akaike info criterion	-5.117018
Sum squared resid	0.015647	Schwarz criterion	-4.866117
Log likelihood	152.8350	Hannan-Quinn criter.	-5.019509
F-statistic	42.81501	Durbin-Watson stat	1.990898
Prob(F-statistic)	0.000000		

Heteroskedasticity Test: ARCH

F-statistic	0.812372	Prob. F(1,54)	0.3714
Obs*R-squared	0.829974	Prob. Chi-Square(1)	0.3623

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/02/15 Time: 03:59
Sample (adjusted): 2000Q1 2013Q4
Included observations: 56 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000446	8.93E-05	4.995388	0.0000
RESID^2(-1)	-0.121722	0.135049	-0.901317	0.3714

R-squared	0.014821	Mean dependent var	0.000398
Adjusted R-squared	-0.003423	S.D. dependent var	0.000533
S.E. of regression	0.000534	Akaike info criterion	-12.19909
Sum squared resid	1.54E-05	Schwarz criterion	-12.12676
Log likelihood	343.5746	Hannan-Quinn criter.	-12.17105
F-statistic	0.812372	Durbin-Watson stat	1.974698
Prob(F-statistic)	0.371422		

7.4) Appendix D: AR (2) Model and Diagnostic Test Results

Figure 25: Correlogram on ARMA (3,2) Model Residuals

Date: 12/30/14 Time: 23:02
Sample: 1999Q1 2013Q4
Included observations: 57

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.241	0.241	3.4790	0.062
		2	-0.135	-0.204	4.5855	0.101
		3	-0.121	-0.036	5.4973	0.139
		4	-0.181	-0.182	7.5788	0.108
		5	0.039	0.123	7.6762	0.175
		6	-0.013	-0.139	7.6871	0.262
		7	0.126	0.207	8.7509	0.271
		8	0.161	0.016	10.537	0.229
		9	-0.201	-0.211	13.367	0.147
		10	-0.361	-0.287	22.714	0.012
		11	-0.059	0.159	22.967	0.018
		12	0.137	0.018	24.376	0.018
		13	0.010	-0.161	24.384	0.028
		14	-0.084	-0.132	24.937	0.035
		15	-0.051	0.020	25.144	0.048
		16	0.028	0.018	25.208	0.066
		17	-0.064	-0.053	25.555	0.083
		18	-0.103	-0.067	26.473	0.089
		19	0.026	-0.127	26.533	0.116
		20	0.125	0.039	27.958	0.110
		21	0.061	0.101	28.310	0.132
		22	-0.117	-0.129	29.615	0.128
		23	-0.021	-0.097	29.657	0.160
		24	0.048	-0.032	29.893	0.188

Dependent Variable: DLCPI
Method: Least Squares
Date: 11/29/14 Time: 14:46
Sample (adjusted): 1999Q4 2013Q4
Included observations: 57 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLCPI(-1)	0.461097	0.127851	3.606530	0.0007
DLCPI(-2)	0.318088	0.125217	2.540289	0.0140
C	0.006801	0.005315	1.279552	0.2062

R-squared	0.568655	Mean dependent var	0.039099
Adjusted R-squared	0.552679	S.D. dependent var	0.041413
S.E. of regression	0.027698	Akaike info criterion	-4.283749
Sum squared resid	0.041426	Schwarz criterion	-4.176220
Log likelihood	125.0869	F-statistic	35.59491
Durbin-Watson stat	1.980417	Prob(F-statistic)	0.000000

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.656681	Prob. F(2,52)	0.200681
Obs*R-squared	3.414394	Prob. Chi-Square(2)	0.181373

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 11/29/14 Time: 14:57
Sample: 1999Q4 2013Q4
Included observations: 57
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLCPI(-1)	-0.852516	0.811458	-1.050597	0.2983
DLCPI(-2)	0.847488	0.721388	1.174801	0.2454
C	-0.001205	0.006487	-0.185753	0.8534
RESID(-1)	0.787486	0.809186	0.973182	0.3350
RESID(-2)	-0.608502	0.381252	-1.596063	0.1165

R-squared	0.059902	Mean dependent var	1.43E-18
Adjusted R-squared	-0.012414	S.D. dependent var	0.027198
S.E. of regression	0.027367	Akaike info criterion	-4.275345
Sum squared resid	0.038945	Schwarz criterion	-4.096130
Log likelihood	126.8473	F-statistic	0.828340
Durbin-Watson stat	1.920396	Prob(F-statistic)	0.513229

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	4.600851	Prob. F(2,54)	0.0143
Obs*R-squared	8.298779	Prob. Chi-Square(2)	0.0158
Scaled explained SS	22.12831	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/02/15 Time: 05:50
Sample: 1999Q4 2013Q4
Included observations: 57

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.64E-05	0.000323	0.143794	0.8862
DLCPI(-1)	0.001432	0.007766	0.184332	0.8544
DLCPI(-2)	0.014627	0.007606	1.923114	0.0597

R-squared	0.145593	Mean dependent var	0.000727
Adjusted R-squared	0.113948	S.D. dependent var	0.001787
S.E. of regression	0.001682	Akaike info criterion	-9.885955
Sum squared resid	0.000153	Schwarz criterion	-9.778426
Log likelihood	284.7497	Hannan-Quinn criter.	-9.844166
F-statistic	4.600851	Durbin-Watson stat	2.287844
Prob(F-statistic)	0.014287		

Chow Breakpoint Test: 2003Q2

F-statistic	6.230316	Prob. F(3,51)	0.001094
Log likelihood ratio	17.79796	Prob. Chi-Square(3)	0.000484

Ramsey RESET Test:

F-statistic	5.345687	Prob. F(2,52)	0.007739
Log likelihood ratio	10.65787	Prob. Chi-Square(2)	0.004849

Test Equation:
Dependent Variable: DLCPI
Method: Least Squares
Date: 11/29/14 Time: 15:24
Sample: 1999Q4 2013Q4
Included observations: 57

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLCPI(-1)	-1.531903	0.688329	-2.225539	0.0304
DLCPI(-2)	-1.249834	0.527682	-2.368536	0.0216
C	0.034041	0.011943	2.850217	0.0062
FITTED^2	91.51502	28.65695	3.193467	0.0024
FITTED^3	-494.6598	151.6409	-3.262048	0.0020

R-squared	0.642217	Mean dependent var	0.039099
Adjusted R-squared	0.614695	S.D. dependent var	0.041413
S.E. of regression	0.025706	Akaike info criterion	-4.400554
Sum squared resid	0.034362	Schwarz criterion	-4.221339
Log likelihood	130.4158	F-statistic	23.33482
Durbin-Watson stat	2.061666	Prob(F-statistic)	0.000000

ARCH Test:

F-statistic	0.143950	Prob. F(1,54)	0.705873
Obs*R-squared	0.148885	Prob. Chi-Square(1)	0.699603

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/29/14 Time: 15:26
Sample (adjusted): 2000Q1 2013Q4
Included observations: 56 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000704	0.000254	2.767155	0.0077
RESID^2(-1)	-0.049938	0.131620	-0.379408	0.7059

R-squared	0.002659	Mean dependent var	0.000667
Adjusted R-squared	-0.015811	S.D. dependent var	0.001745
S.E. of regression	0.001758	Akaike info criterion	-9.813893
Sum squared resid	0.000167	Schwarz criterion	-9.741559
Log likelihood	276.7890	F-statistic	0.143950
Durbin-Watson stat	1.969625	Prob(F-statistic)	0.705873

7.5) Appendix E: TAR(2) Model and Diagnostic Test Results

```
library("car")

library("tseries")

library("TSA")

library("lmtest")

library("FinTS")


# importing datas and mining

z<-read.table("TurkeyData.csv",header = T,sep = ";")

z<-z[,-c(6,7,8)]; z<- data.matrix(z)

data<- z[,-1]; data[,1] <- data[,1]/100 + 1

colnames(data)<- c("GDP","CPI","M","XRE")


dates<- sapply(1999:2013, function(x) paste0(x,"Q",1:4)); dates<-dates[-1]

ldata<- log(data)

ldata<- ldata[,c(2,1,3,4)]


dlcpi<- diff(ldata[,1])

tarModel<-tar(dlcpi,p1 =  2, p2 = 2,d =  1, is.constant1 = T, is.constant2 = T, estimate.thd =
TRUE, print = T)

xDat<- matrix(c(tarModel$dxy1,tarModel$dxy2),dim(tarModel$dxy1)[1])


jbtest<- jarque.bera.test(tarModel$residuals); jbtest$statistic; jbtest$p.value

bgTest<-bgtest(dlcpi[-c(1,2)] ~ xDat , order = 2, type = c("Chisq", "F"))

ARCHtest <- ArchTest(tarModel$residuals,lags = 1)

RESETtest<-resettest(dlcpi[-c(1,2)] ~ xDat, power = 1)

BPtest<- bptest(dlcpi[-c(1,2)] ~ xDat)



statsTAR<-t(matrix(c(jbtest$statistic,jbtest$p.value,bgTest$statistic,
```

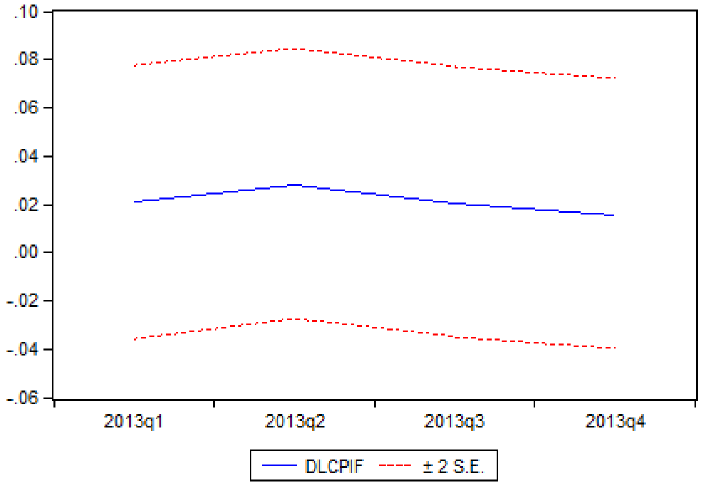
```
bgTest$p.value,BPtest$statistic,BPtest$p.value,

RESETtest$statistic,RESETtest$p.value,ARCHtest$statistic,ARCHtest$p.value),2,5))

binTar <- rep("Not Reject",5); binTar[statsTAR[,2]<.05]<-"Reject"

NullsTAR<- c("Normality","No serial correlation","Homoscedastic","Correct
Specification","No ARCH Effect")

repTAR<- matrix(c(round(statsTAR,4),NullsTAR,binTar),5,4); rownames(repTAR) <-
c("Jarque Bera", "LM Test", "Breusch-Pagan Test", "RESET Test", "ARCH Test")

colnames(repTAR) <- c("Statistic Value", "P-value",        "H0", "Reject / Not Reject H0")
```

Figure 26: Correlogram of TAR(2) Model Residuals

Date: 01/01/15 Time: 22:06
Sample: 1999Q1 2013Q4
Included observations: 57

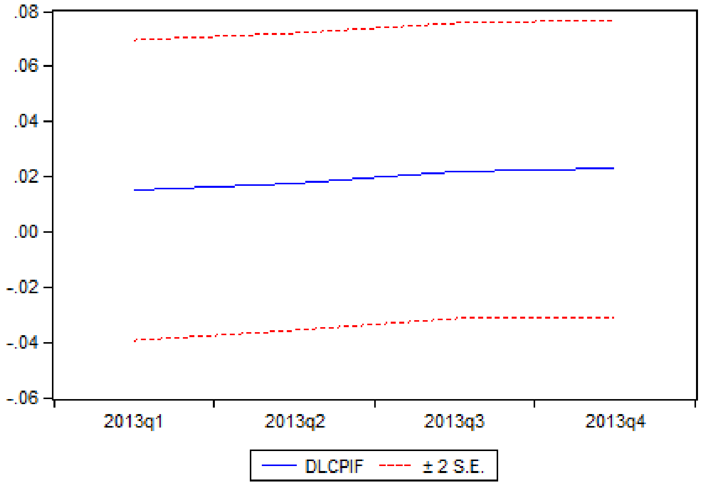
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.165	-0.165	1.6280	0.202
		2	0.053	0.026	1.7968	0.407
		3	-0.143	-0.134	3.0682	0.381
		4	-0.000	-0.047	3.0683	0.546
		5	-0.047	-0.049	3.2139	0.667
		6	0.157	0.131	4.8450	0.564
		7	-0.018	0.024	4.8674	0.676
		8	0.180	0.174	7.0814	0.528
		9	-0.120	-0.032	8.0835	0.526
		10	-0.156	-0.194	9.8309	0.455
		11	0.010	0.008	9.8385	0.545
		12	0.184	0.189	12.381	0.416
		13	-0.170	-0.180	14.583	0.334
		14	0.012	-0.130	14.594	0.406
		15	-0.224	-0.207	18.607	0.232
		16	0.071	0.010	19.023	0.267
		17	-0.080	-0.043	19.563	0.297
		18	0.041	-0.031	19.709	0.349
		19	-0.049	-0.078	19.922	0.399
		20	0.068	-0.041	20.346	0.436
		21	-0.038	0.152	20.481	0.491
		22	0.010	0.110	20.492	0.552
		23	-0.102	-0.132	21.520	0.549
		24	0.105	-0.018	22.634	0.541

7.6) Appendix F: Forecast Results



Forecast: DLCPIF	
Actual: DLCPI	
Forecast sample: 2013Q1 2013Q4	
Included observations: 4	
Root Mean Squared Error	0.010117
Mean Absolute Error	0.009221
Mean Abs. Percent Error	64.82807
Theil Inequality Coefficient	0.247340
Bias Proportion	0.109135
Variance Proportion	0.034371
Covariance Proportion	0.856495

Figure 27: Forecast of AR(2) Model



Forecast: DLCPIF	
Actual: DLCPI	
Forecast sample: 2013Q1 2013Q4	
Included observations: 4	
Root Mean Squared Error	0.007746
Mean Absolute Error	0.006674
Mean Abs. Percent Error	46.94333
Theil Inequality Coefficient	0.200028
Bias Proportion	0.030631
Variance Proportion	0.162596
Covariance Proportion	0.806772

Figure 28: Forecast of TAR(2) Model

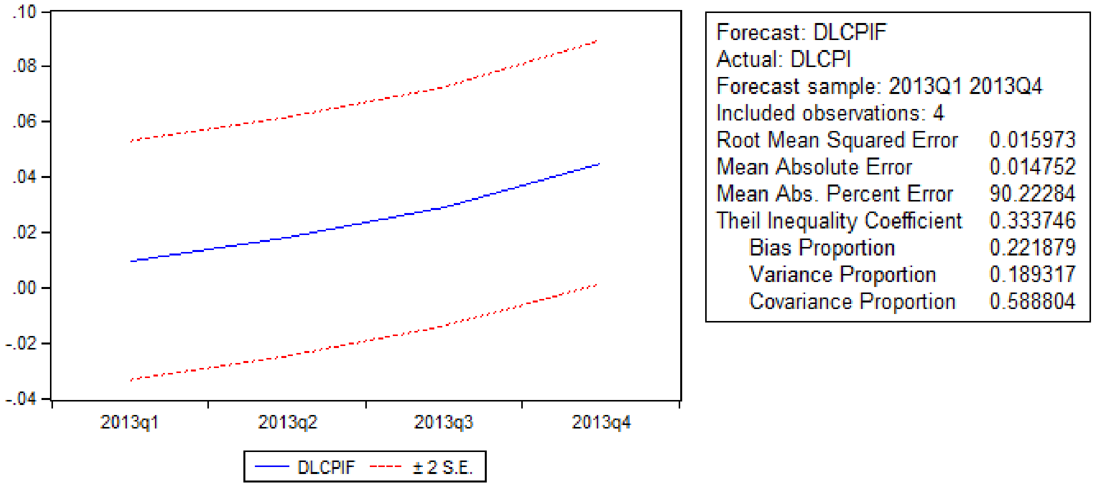


Figure 29: Forecast of Maliszewski's Equation Model