MODELLING TERM STRUCTURE, EXCHANGE RATE AND INTEREST RATE IN TURKISH ECONOMY

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ABSTRACT

Nowadays, deciding upon the appropriate model to be analyzed in econometrical model is still an important area of research. In this study, we analyze the structure of the models regarding the data of Turkish Treasury bond and exchange rate return for the crisis, which occur in the year 2000 and the post-crisis era, both in short run and long-run case. In order to study every aspects of the issue, we analyze linear and nonlinear models by including error correction equation in each model and by excluding it. We conclude that there is a nonlinear tendency in both short run and long run case where we use Markov Switching Model; more specifically, in short run case, there is a tendency towards regime changes in variance and intercept term while in long run, this is towards regime changes in variance, intercept and coefficients.

ÖZETÇE

Günümüzde, uygun modele karar vermek, ekonometrik modellerin incelenmesinde hala önemli bir araştırma alanıdır. Bu calışmada 2000 krizi ve kriz sonrası dönem için Türkiye Hazine bonoları ve döviz kuru verilerine ilişkin modellerin yapılarını hem kısa dönem hem de uzun dönemde inceledik. Sorunu bütün yönleriyle inceleyebilmek için doğrusal ve doğrusal olmayan modelleri, hata düzeltme modellerini ekleyerek ve çıkartarak inceledik. Markov Aktarma Modelini kullandığımız kısa ve uzun dönemlerde doğrusal olmayan bir eğilim olduğu sonucuna vardık; daha spesifik olmak gerekirse, kısa dönemde kesim noktası ve varyans terimlerindeki rejim değisikliğine eğilim varken, uzun dönemde bu eğilim kesim noktası, varyans ve katsayılardakilardaki rejim değişikliğine doğrudur.

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Contents

1 INTRODUCTION

The purpose of this study is to decide on the most accurate model whether it is linear or non-linear by testing the performance of ex ante and ex post forecasting for the data of exchange rate and sovereign spread. This decision process illustrates the linear or regime switching manner of exchange rate and sovereign spread's movement. Also, in this process, we take forecasting performance as an indicator of these movements.

In our analysis, the data we used are from 2000 to 2006; therefore the data is heavily affected by the fluctuations in Turkish economy. The stand-by agreement that was signed with IMF in the late 1999 was failed due to the overvaluation of currency which then, led to increased imports together with high current account deficit. This inflation standardization program based on a fixed exchange rate with the direct effect of political instability originated the crisis in February 2001. After 2001, Central Bank adapted a floating exchange rate regime. After the liberalization in Turkish economy, the question raised that whether there exists contagion between exchange rate and sovereign spread or not, and in this study we are dealing with this question.

P. Rowland (2004) stated that some of the studies handle sovereign spread as spread of emerging market bond index, some are a benchmark bond for each country or some are the spread of individual bonds. We focus on weekly data with maturities 90 and 360 days, and take spread of individual bonds return as sovereign spread.

We found that the spread between foreign and domestic bond returns yields information about the behavior of exchange rate and exchange rate is an indicator of these financial assets. Using secondary market data with maturities 90 days and 360 days, we analyze both short term and long term structure of exchange rate return, and secondary market US Treasury bond, domestic bond and euro-bond returns. We deal with Vector Autoregressive (VAR) model and Vector Error Correction Model (VECM) as linear model, and Markov Switching Vector Autoregressive (MS-VAR) and Markov Switching Vector Error Correction Model (MS-VECM) as non-linear model to stress structural changes and regime shifts. In this paper, we argue that in general Markov Switching models give better forecasting result than linear models for short term and long term data set. Also, linearity test results and information criteria test statistics indicate the same conclusion with our assumption.

The rest of article is organized as follows. In the second section, we introduce literature briefly. In the third section, we mention the methodology of the system. In the fourth part, we display our data and provide empirical findings about the interest rates and exchanged rates of Turkey: linearity test results and error statistics of static and dynamic forecast result both for linear and non linear models. Finally, in the last section, we present our conclusion together with the summary of our results.

2 LITERATURE REVIEW

In the study of O. P. Ardıç and F. Selçuk(2004) that examined exchange rate dynamics for the post-crisis period in Turkey, the relationship between emerging market bonds and US treasury bills for Turkey is demonstrated by using daily data from March 2001 to October 2003. They concluded that the stabilization of the volatility of exchange rate was accomplished by the policies of Central Bank. Moreover, they illustrated that emerging market bonds and US treasury bills are explanatory variable for nominal exchange rate dynamics. They analyzed the variables based on daily data as the TRL/ USD exchange rate return, EMBI spread, the absolute value of the exchange rate return as a measure of volatility, the change Central Bank overnight interest rates, the daily total amount bought by the central bank in USD selling auctions, by using VAR model. We extend this analysis by using linear and non-linear models through comparing reliability of forecasting results with weekly data.

P. Rowland (2004) revealed in his paper that there is a relation between sovereign spread and exchange rate, US stock market, the spread of other emerging markets, by using daily data. This result was obtained by using OLS method for daily data and concluded that there exist contagion, changes in US Stock Market and in Colombian Exchange Rate effects spread. In addition to this, considering monthly data, sovereign spread is strongly related with exchange rate, economic growth rate and US T- Bill rate. For this case, Johansson framework of multivariate cointegration method is used. P. Rowland analyzed daily data as short-run case and monthly data as long-run case. He constructed both short and long run return of Emerging Market Bond Index Global Colombia spread variables, as a measure of the Colombian sovereign spread. Moreover, Budina and Mantchev (2000) analyzed the relation between external and internal determinants of Brady Bond prices in secondary market by using error correction model. They reached the solution that gross foreign reserves, exports affect Brady Bonds positively, real exchange rate and Mexican nominal exchange rate depreciation affect Brady Bonds negatively. Although the studies about sovereign spread determinants were generally based on monthly data, we use weekly data in our analysis. Furthermore, different from above studies, we use both linear and regime switching model to observe the determinants of spread.

O. Culha, F. Ozatay and G. Sahinbeyoglu (2006) focused on daily data from 1997 to 2004 and monthly data from 1998 to 2004 of sovereign bonds in secondary markets of 21 emerging countries. They considered both daily and monthly data by using individual country and panel estimation methods to observe the determinants of spread. For both frequency and estimation methods, they concluded that contemporaneous change in the US corparate bond spread influence short-run fluctuation of the EMBI spread.

Additionally, exchange rate risk and weighted average of Turkish treasury action interest rates are also studied in the paper named 'Exchange rate risk and interest rate: A Case Study for Turkey' by H. Berument and A. Gunay (2003). This paper takes monthly data from 1986 to 2001 and uses Generalized Autoregressive Conditional Heteroscedastic (GARCH) model to show that Turkish Treasury auction is affected the exchange rate positively. Unlike our paper, interest rates are taken from primary market, and foreign interest rates are not included into the model.

We mentioned in the introduction that we deal with VAR Model and VECM as linear model, and MS-VAR and MS-VECM as non-linear model to stress structural changes and regime shifts. There are several studies done by using MS-VECM in the literature. H.M. Krolzig, M. Marcelling, and G. E. Milton (2000) analyzed the relationship of UK labor Market with MS-VECM model to argue in sample and out of sample forecasting behaviors by using seasonally adjusted quarterly data from 1965 to 1993. They concluded that forecasting performance of Markov Switching Intercept Heteroscedastic Vector Error correction Model (MSIH-VECM) is better than VECM. Also, MS-VECM model was examined by R.H. Clarida, Lucia Sarno, M.P. Taylor, G. Valente(2002) by using weekly dollar exchange rate for four G5 countries from 1979 to 1998. They found that MS-VECM exchange rate model give better results in forecasting than in random walk and linear VECM exchange rate model. Furthermore, P. Kostov and J. Lingard(2004) deal with long-run equilibrium of the UK meat consumption in the period 1974- 2000, and explain shifts in the meat consumption within the UK consumption system by using Markov Switching models. Unlike this paper, we not only touch on the main model, but also mention the future behavior of the model.

3 METHODOLOGY

3.1 Model Specification

After globalization of the world, there are spillovers and contagion on different markets. They need to be analyzed by using vector or multivariate time series analysis to cover much new ground of the markets. In our study, we first construct linear and non-linear model and then, decide on the appropriate model through comparing forecasting error statistics and related linearity tests. We begin with Vector Autoregressive Model (VAR) as a linear model which is a vector modeling approach due to C. A. Sims (1980) work.

Let y_t be a 3X1 vector consisting variables as logarithmic values of exchange rate, domestic & euro-bond of Turkey. VAR (p) model has the following form for y_t:

$$y_t = v_t + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + ... + \Gamma_p y_{t-p} + u_t \tag{1}$$

$$\begin{aligned} E(u_t) &= 0; \\ E(u_t u_t) &= \left\{ \begin{array}{ll} \Omega & for\ t = \tau \\ 0 & otherwise \end{array} \right\} \end{aligned}$$

with Ω (3X3) symmetric positive definite matrix. u_t is a generalization of white noise vector. Γ_i , a 3X3 matrix, is the coefficient of corresponding endogenous variable of y_i $\forall i = 0, 1, ..., p$.

US treasury bond is included in our system as an exogenous variable and we analyze contemporaneous and lagged effect on the system, so VAR (p) model with exogenous variables are seen in the equation as follows:

$$y_t = v_t + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + ... + \Gamma_p y_{t-p} + \Psi_1 x_t + ... + \Psi_m x_{t+1-m} + u_t \tag{2}$$

x_t denotes the exogenous variable, US treasury bond and Ψj, 3X1 matrix, is the coefficient of the corresponding variable x_{t-j} $\forall j = 0, 1, ..., m$.

The main concept of cointegration process was developed by Granger (1983) and Engle and Granger (1987). An error correction model for VAR (p) model as we stated in equation (2) can be represented as:

$$\triangle y_t = v_t + \sum_{i=1}^{p} \Gamma_i \triangle y_{t-i} + \sum_{j=1}^{m} \Psi_j \triangle x_{t+1-j} + \Pi \ [y_{t-1} : x_{t-1}] + u_t \tag{3}$$

$$\begin{aligned} E(u_t) &= 0; \\ E(u_t u_t) &= \left\{ \begin{array}{ll} \Omega & for\ t = \tau \\ 0 & otherwise \end{array} \right\} \end{aligned}$$

$[yt : xt]$ is a nonstationary vector but, I (1) process of the vector is stationary and $\Pi = \alpha\beta$' is the 3Xr cointegrating matrix where r can be up to the number of variables minus one.

In literature, the bilinear models of Granger and Andersan (1978), the treashhold autoregressive (TAR) model of Tong (1978) the state dependent model of Priestly (1980) and the Markov Switching model of Hamilton(1989) were examples of nonlinear models. (Tsay,p.155) We continue on our analysis by using Markov Switching models.

The main idea of this nonlinear model is that different subsamples could be adopted different time series process for a given variable. (Hamilton, p.690) Consider a VAR(p) model as we mentioned in equation 2, in which both the intercept and the vector autoregressive coefficients differ for different subsamples. Therefore, due to Hamilton (1989) work, Markov Switching Intercept Vector Autoregression (MSI-VAR) model can be written as:

$$\triangle y_t = v(s_t) + \sum_{i=1}^{p} \Gamma_i(s_t) \triangle y_{t-i} + \sum_{j=1}^{m} \Psi_j(s_t) \triangle x_{t+1-j} + u_t \tag{4}$$

where $u_t \sim NIID(0, \sum_u)$ and s_t is a discreate valued random variable which is i.i.d.

Markov Switching Vector Error Correction model was developed to MSIH- VECM by Krolzig(1997), where I denotes intercept, H denotes heteroscedasticity. For a VAR (p) model the equation becomes

$$\triangle y_t = v(s_t) + \sum_{i=1}^{p} \Gamma_i(s_t) \triangle y_{t-i} + \sum_{j=1}^{m} \Psi_j(s_t) \triangle x_{t+1-j} + u_t \tag{5}$$

where $u_t \sim NIID(0, \sum_u(s_t))$

Let the number of states in Markov Switching Process be N. The intercept term and similirlay the other terms follow the below state:

$$v(s_t) = v_{s_t} = \left\{ \begin{array}{c} v_1 \quad \text{if} \quad s_t = 1 \\ . \\ . \\ v_N \quad \text{if} \quad s_t = N \end{array} \right\}$$

An Ergodic Markov Chain is the stochastic process that reveal all the regimes. The states in MS process can be displayed by the transition probabilities:

$$\begin{aligned} Pij &= \Pr(st + 1 = j/st = j), \\ \sum_{i=1}^{m} p_{ij} &= 1 \qquad \forall i, j = 1, 2, ..., N \end{aligned}$$

The transition probabilities could be also represented in a transition matrix, P. For p_{ij}, the "$_j$" corresponds to the value on the row and "$_i$" corresponds to the value in the column.

H. M. Krolzig, M. Marcellino, G. E. Mizon (2000) stated in their paper that "Markov Switching Intercept Vector Error Correction Model(MSI_VECM) exhibits equilibrium as well as error correction mechanism: in each regime disequilibria are adjusted by the vector equilibrium correction mechanism; since the regimes themselves are generated by statinary, irreducible Markov Chain; errors arising from regime shifts themselves are corrected towards the stationary distribution of regimes." We also interested in the change of the long run equlibrium depending on the regime changes so, we focus on the regime dependency of error correction term. Markov Switching vector error correction model can be written as below:

$$\triangle y_t = v(s_t) + \sum_{i=1}^{p} \Gamma_i(s_t) \triangle y_{t-i} + \sum_{j=1}^{m} \Psi_j(s_t) \triangle x_{t+1-j} + \Pi(s_t)\left[y_{t-1} : x_{t-1}\right] + u_t \tag{6}$$

where $\Pi(s_t)$ =$\alpha(s_t)\beta$'

3.2 Forecasting

While analysing time series, many studies evaluate the in sample and the out of sample behavoiur of the data. For the out of sample analysis, forecasting is the appropriate tool to investigate the results. If there are more than two forecast errors then, 'mean of the forecast errors', 'standard deviation of the forecast errors', 'forecast tests single chi2 (.)', 'root mean square error' and 'Mean absolute Percentage Error' statistics exist. We compare the models on the basis of root mean square (RMSE) and absolute prediction errors (MAPE), which are used in measuring accuracy of forecast.

After constructing linear and non linear models, we continue on our analysis by evaluating forecasting results. Forecasting can be done in two ways; static (ex post) and dynamic (ex ante). Static forecasting is 1-step ahead forecast where observed values are the basis of the lagged information. Whereas, dynamic forecasting is h-step ahead forecast where former forecasts are reprocessed. For ex post forecasting, the VAR(p) equation with exogeneous varibles can be represented as below (See Clements and Hendry, 1998a, 1998b):

$$\triangle \hat{y_t} = \sum_{i=1}^{p} \hat{\Gamma_i} \triangle y_{t-i} + \sum_{j=1}^{m} \hat{\Psi_j} \triangle x_{t+1-j} \tag{7}$$

In dynamic forecasting, we only need observed values of variables which are contemporaneously included in the system. In our study, the values of $\triangle$xt are necessary for t=T+1,. . . .,T+H. For dynamic forecasting, the VAR(p) equation with exogeneous variables can be represented as:

$$\triangle \hat{y_t} = \sum_{i=1}^{p} \hat{\Gamma_i} \triangle \hat{y_{t-i}} + \sum_{j=1}^{m} \hat{\Psi_j} \triangle x_{t+1-j} \tag{8}$$

For non linear models, static and dynamic forecasting follow the same procedure as in linear models. H.M. Krolzig(2000) stated the procedure in his study "Predicting Markov- Switching Vector Autoregressive Processes" . Let N be the number of states in a Markov Switching model. For all N models, we need to provide the forecasting results in both static and dynamic forecasting. Also, let ξ_t be the filtered probabilities of the model. The corresponding regime probabilities $\hat{\xi_{t|t}}$ are calculated below where P is the transition probabilities of the model:

$\hat{\xi_{t+1|t}} =$ P' ξ_t

To be more specific, we illustarate this procedure for static forecasting and we take the MSI-VAR model. For simplicity, we take the number of regimes as N=2. So s_1 and s_2 denotes the states of the model.

$$\triangle \hat{y_t} = v(s_1) + \Gamma_j(s_1)\hat{} \triangle y_{t-1} + \Psi_j(s_1)\hat{} \triangle x_{t+1-j} \qquad ...first\ state$$

$$\triangle \hat{y_t} = v(s_2) + \Gamma_j(s_2)\hat{} \triangle y_{t-1} + \Psi_j(s_2)\hat{} \triangle x_{t+1-j} \qquad ...\sec ond\ state$$

The above equations represent the results of the static forecasting for both the first and the second regime. We first multiply the forecasting value in the i^{th} regime and the corresponding probability $\hat{\xi_t}$ in ith state and afterwards, we add the results of the two states to obtain forecasting results . Since we took N=2, the probabilities can be represented as ($\hat{\xi_{1t}}, \hat{\xi_{2t}}$) for the corresponding time value,t. Final forcasting result can be represented as follows:

$$\triangle \hat{y_t} = (v(s_1)\hat{\xi_{1t}} + v(s_2)\hat{\xi_{2t}}) + (\Gamma_1(s_1)^{\hat{}}\,\hat{\xi_{1t}} + \Gamma_j(s_2)^{\hat{}}\,\hat{\xi_{2t}})\triangle y_{t-1} + (\Psi_j(s_1)^{\hat{}}\,\hat{\xi_{1t}} + \Psi_j(s_2)^{\hat{}}\,\hat{\xi_{2t}})\triangle x_{t+1-1} \tag{9}$$

For dynamic forecasting, we apply the similiar method as in linear model. We took N=2 and the results of two regimes are evaluated. The equations below represent the procedure of dynamic forecasting for MSI-VAR model in two states:

$$\triangle \hat{y_t} = v(s_1) + \Gamma_j(s_1)^{\hat{}} \triangle \hat{y_{t-1}} + \Psi_j(s1)^{\hat{}} \triangle x_{t+1-j} \qquad ...first\ state$$

$$\triangle \hat{y_t} = v(s_2) + \Gamma_j(s_2)^{\hat{}} \triangle \hat{y_{t-1}} + \Psi_j(s2)^{\hat{}} \triangle x_{t+1-j} \qquad ...\sec ond\ state$$

As we mentioned above, the former results of the forecasting values of endogeneous variables are entered into the system. The same procedure is applied to the forecasting results of the states above as in static forecasting. ($\hat{\xi_{1t}}, \hat{\xi_{2t}}$) denotes the regime probabilities for the corresponding time t . Then,the final forecasting result is as follows:

$$\triangle \hat{y_t} = (v(s_1)\hat{\xi_{1t}} + v(s_2)\hat{\xi_{2t}}) + (\Gamma_1(s_1)^{\hat{}}\,\hat{\xi_{1t}} + \Gamma_j(s_2)^{\hat{}}\,\xi_{2t})\triangle \hat{y_{t-1}} + (\Psi_j(s_1)^{\hat{}}\,\hat{\xi_{1t}} + \Psi_j(s_2)^{\hat{}}\,\hat{\xi_{2t}})\triangle x_{t+1-1} \tag{10}$$

The only difference of error correction models from VAR model is that cointegration equations are included into the main equations during forecasting evaluation. While in static forecasting,cointegration equations are entered into the system with their observed values, in dynamic forecasting the procedure is performed with forecasting values.

In dynamic procedure, y and x are variables and c be the constant term. The below equation gives the cointegration relation with a constant term.

$$\zeta_t = c + y_{t-1} + x_{t-1}$$

Taking the difference of the eqaution yields the following results:

$$\hat{\zeta_t} = \Delta y_{t-1} + \Delta x_{t-1} - \zeta_{t-1}$$

For dynamic forecasting, error correction term is entered the system as follows:

$$\triangle \hat{y_t} = \sum_{i=1}^{p} \hat{\Gamma_i} \triangle \hat{y_{t-i}} + \sum_{j=1}^{m} \hat{\Psi_j} \triangle x_{t+1-j} + \hat{\Pi} \, \hat{[y_{t-1} : x_t]} \tag{11}$$

The error correction model in non linear models is same as the error correction model in linear models. In static forecasting, the procedure is performed with observed values whereas, in dynamic forecasting, the cointegration equations are evaluated with forecasting values. While explaning forecasting procedure of markov switching VAR models, we took two states for simplicity. Likewise, we take two as the regime number. Dynamic forcasting for MSIH-VECM in two states can be represented as below:

$$\triangle \hat{y_t} = v(s_1) + \hat{\Gamma_j(s_1)} \triangle \hat{y_{t-1}} + \hat{\Psi_j(s_1)} \triangle x_{t+1-j} + \Pi(s_1)' \, [y_{t-1} : x_t]' \qquad ...first$$

state

$$\triangle \hat{y_t} = v(s_2) + \hat{\Gamma_j(s_2)} \triangle \hat{y_{t-1}} + \hat{\Psi_j(s_2)} \triangle x_{t+1-j} + \Pi(s_2)' \, [y_{t-1} : x_t]' \qquad ...\sec ond$$

state

Following multiplication and addition process as in MS-VAR model, the final forecasting result becomes as below if we take ($\hat{\xi_{1t}}, \hat{\xi_{2t}}$) as the regime probabilities for the corresponding time values, t :

$$\begin{aligned} \triangle \hat{y_t} &= (v(s_1)\hat{\xi_{1t}} + v(s_2)\hat{\xi_{2t}}) + (\Gamma_1(s_1)^{\hat{}}\,\hat{\xi_{1t}} + \Gamma_j(s_2)^{\hat{}}\,\hat{\xi_{2t}}) \triangle \hat{y_{t-1}} \\ &\quad +(\Psi_j(s_1)^{\hat{}}\,\hat{\xi_{1t}} + \Psi_j(s2)^{\hat{}}\,\hat{\xi_{2t}}) \triangle x_{t+1-1}+) + (\Pi(s_1)'\hat{\xi_{1t}} + \Pi(s_2)'\hat{\xi_{2t}})\,[y_{t-1} : x_{t-1}]^{\hat{}} \end{aligned} \tag{12}$$

4 EMPRICAL RESULTS

In this section, we illustrate the result of the analysis we have done. In the following subsection, we mention about the time series properties of the data. In the second subsection, we represent the results of the data with maturities 90 days. Additionally, the final subsection is where we display the empirical results of the data with maturities 360 days.

4.1 The Data

In their study, E. Girardin and Z. Liu (2003) mentioned that there were many papers using daily data over different time period but, these papers could not reach any cointegration or relation between Chinese stock market and other foreign stock markets. However, by using weekly data, they demonstrated the cointegration of Shangai A-share market index with either Hang Seng index after the Asian Crisis or Standard' s and Poor's 500 index before the Asian Crisis. Likewise, we study with monthly[1] data but, we are unable to get reliable cointegration relation on them; so, we focus on the weekly data.

As we mentioned in section 1, we analyze weekly data of US Treasury bond, domestic bond, euro-bond which we first add one to each and then, deal with their logarithms while, logarithmic values of exchange rate[2] is involved into the system directly. As a weekly data, we take 5-days data and calculate the weighted average of them. Furthermore, as an exchange

[1] Montly data are also studied and lag length criteria give 1-1-8 lags for SC, HQ, AIC respectively both for short-run and long-run. There are two cointegration relations for lag 1 and six cointegration relations for lag 8 which are the same for both model.

[2] In our analysis, we remove the exchange rate variable and analyze again both for long-run and short-run. There is no cointegration tested for all given length lag criteria except data set with maturity 90 with lag order 1.

rate variable, we consider TL/USD nominal exchange rate. Data are collected from the database of the company Riskturk. (www.riskturk.com.tr) The logarithmic variables of euro bond, exchange rate, US Treasury bond and domestic bond are denoted as leuro, le, lus and ltl respectively.

G.Sahinbeyoglu and C. Yalcin declared that "The maturity structure of primary and secondary market structure of governments bond and bill have similar trend. A yield of six month maturity is evaluated as relatively longer term for Turkish case." To analyze both short and long run relationship of exchange rate and sovereign spread, we undertake secondary market data with maturities 90 and 360. We will first study on the data with maturity 90 days in part 1 and then on the data with maturity 360 days in part 2.

4.1.1 Time series analysis of short run data

To begin with time series analysis, we first check the stationary analysis. Table 1 represents Agumented Dickey- Fuller (ADF) test results. The result of stationary analysis using ADF test is that null hypothesis is rejected at 1 percent significance level for all variables but, the first difference of the variables are stationary at this level. Intercept term and trend involve in the ADF tests at level, but trend does not involve in the ADF test in the first level. Moreover, we apply Phillips and Perron (PP) test which has the same results with the ADF test. (see Table2) While modeling, we focus on the first differences of the variables; exchange rate, euro bond, domestic treasury bond and US treasury bond denoted as de, deuro, dtl, dus, respectively.

Before modeling the system and establishing cointegration relation, we have to choose lag-length of the model. Three model selection criteria as Akaike Information Criteria (AIC), Schwarz Criteria (SC) and Hannan Quinn Criteria (HQC) up to lag order 8 are displayed in Table(3). In that table, we choose the smallest lag given by SC which is two and the other model selection criteria AIC and HQ give lags as 6 and 3 respectively.

4.1.2 Time series analysis of long run data

In the long run analysis, we begin with stationary analysis of the data with maturities 360 days. Table (4) represents ADF test results with level and I (1) process. The test results show that all variables are non stationary but, they are stationary at first differences. Moreover, the same procedure in short run case is applied to trend and intercept term. Alternatively, PP tests results give the same results as displayed in Table (5).

Table (6) presents Akaike Information Criteria (AIC), Schwarz Criteria (SC) and Hannan Quinn Criteria (HQC) results up to lag order 8. In that case, SC, HQ, AIC give the results 2, 5 and 6 respectively. We choose lag two which is the smallest one.

4.2 Short-run Analysis

The main purpose of this study is to select the model by comparing forecasting accuracy of the model and by focusing on the related linearity tests results. Thus, we only display forecasting result of the model, instead of the model itself. We first consider short run dynamics of our models and display error statistics of static and dynamic forecasting results of the the linear and non-linear models. As we mentined in section three, root mean square error (RMSE) and mean absolute percentage error(MAPE) are used in measuring accuracy of forecasting. Thus, we focus on RMSE and MAPE as our error statistics of forecasting results. Then, we continue on our study stating forecasting adequacy by comparing the error term of all models. Linearity test results are then evaluated.

4.2.1 Model Setting of short run data

We did the stationary analysis and resulted that all the data follow I (1) process from week 3 of 2000 to week 44 of 2006. Then, we chosed the lag-length criteria as SC in subsection one which gave us the result as second lag. Thus now, as our linear model, we will focus on VAR (2) model. In our study, we observe the effect of constant term on the spread; therefore, this constant term is included in the error correction equation but not exist in the main equation. So, we apply the data to equation (2) with p=2, m=1 and no constant term. In order to point the best model, we collect both dynamic and static forecasting results in the Table(7) for VAR model. This table shows 1-step, 4-step, 8-step and 12-step error statistics of ex ante and ex post forecasting results.

The rank of a cointegration gives the number of linear combinations of the system which are stationary. The rank of the cointegration system is estimated by using the logarithmic likelihood ratio test. While applying rank test, we first analyze the data set with a constant term and then, exclude this constant term and analyze the data set without a constant term. I(1) cointegration analysis yields that there are two cointegration relationships for both cointegration equation; with a constant term and without a constant term in the equation. Table (8) display the results of cointegration tests.

In our analysis, we focus on the spread on Turkey Treasury bond and US Treasury bond. We take domestic bond return and euro bond return for Turkey case and take domestic bond return for US case. By this way, we are able to see how the risk free bonds are exposed to the country risk. Our assumption is that first cointegration is the spread between domestic Treasury bond return and US Treasury bond return. Also, second cointegration is the spread between euro-bond return for Turkey and US Treasury bond return. We take the equation with constant term as a first case and the equation with no constant as a second case.

Cointegration equation with a constant term:

$$ltl_t - lus_t = -0.18660 + \xi_{1,t+1}$$

$$leuro_t - lus_t = -0.021423 + \xi_{2,t+1}$$

Cointegration equation without a constant term:

$$\begin{aligned} ltl_t - lus_t &= \xi_{1,t+1} \\ leuro_t - lus_t &= \xi_{2,t+1} \end{aligned}$$

To see long run equilibrium of the model, we handle vector error correction model (VECM). In our analysis, we also consider cointegration relation without a constant term. Table (9) and Table(10) represent the error statistics of forecasting results of VECM with a constant term in the cointegration equation and VECM with no constant term in the cointegration equation respectively. Similar to Table (8), Table (9) and Table(10) display 1-step, 4-step, 8-step and 12-step ex ante and ex post forecasting results.

We mentioned in the third section that we took Markov Switching model as non linear models. We will continue our analysis by focusing on the state dependency of variables and error terms. We concentrate on the regime changes in intercept term for VAR model and for both VEC models. We obtain MSI- VAR model for VAR model, and MSI-VECM for both VEC models. Error statistics of forecasting results of MSI-VAR model display in Table(11) with 1-step, 4-step, 8 step and 12-step both in ex ante and ex post forecasting. Also, Table(12) and Table(13) represent error statistics of forecasting results of MSI-VECM with a constant term in cointegration relation and MSI-VECM model without a constant term in error correction term, respectively. Similiar to Table(11), static and dynamic forecasting results and all step prediction are illustrated.

Then we carry forward our analysis by examining regime switches in intercept term and in variance. We handle MSIH- VAR model and MSIH- VECM model for both VEC models. Table (14) represents error statistics of static and dynamic forcasting results of MSIH-VAR model with 1-step. 4-step, 8-step and 12-step prediction. Table (15) and Table (16) present error statistics of ex ante and ex post forecasting results of MSIH-VECM with a constant term in the error correction term and MSIH-VECM without a constant term in the error correction term,respectively, including all step predictions.

Finally we advance our study by investigating state changes in intercept term, variance and all coefficients in the model. Error statistics of forecasting results of MSIH-VAR model with 1-step, 4-step, 8-step and 12-step prediction can be seen in Table(17), both in static and dynamic forecasting. Likewise, Table(18) and Table(19) demonstrate error statistics of ex ante and ex post forecasting results of MSIH-VECM with a constant term in error correction term and without a constant term in error correction term with all step of prediction, respectively.

4.2.2 Model comparision of short run data

Initially, we decide on the appropriate model for the variables by comparing the error terms of static and dynamic forecasting results. After that, we evaluate the linearity test results and model selection criteria test results of the models.

We first analyze the RMSE and MAPE statistics of forecasting results of the models. We take the smallest value of the error statistics to choose the most appropriate model for given step predictions. In Table (20), the proper model is illustrated for 1-step, 4-step, 8-step, 12-step prediction and table contains both static and dynamic forecasting results. In dynamic forecasting, we deduct the result that only exchange rate variable follow linear model in 1-step, 4-step and 12-step predictions. For exchange rate variable, the congruent models obtained from the comparison among the RMSE statistics and among the MAPE statistics of dynamic forecasting results are displayed in Figure 1 and Figure 2 respectively, for all 1-step, 4-step, 8- step and 12-step predictions.

Figure 1 illustrates the proper model chosen by comparing RMSE statistics of dynamic forecasting. 1-step, 4-step, 8-step and 12-step predictions represents VECM with a constant term in the error correction equation, MSVAR with regime changes in the intercept term, MSVECM without a constant term in error correction equation and with regime

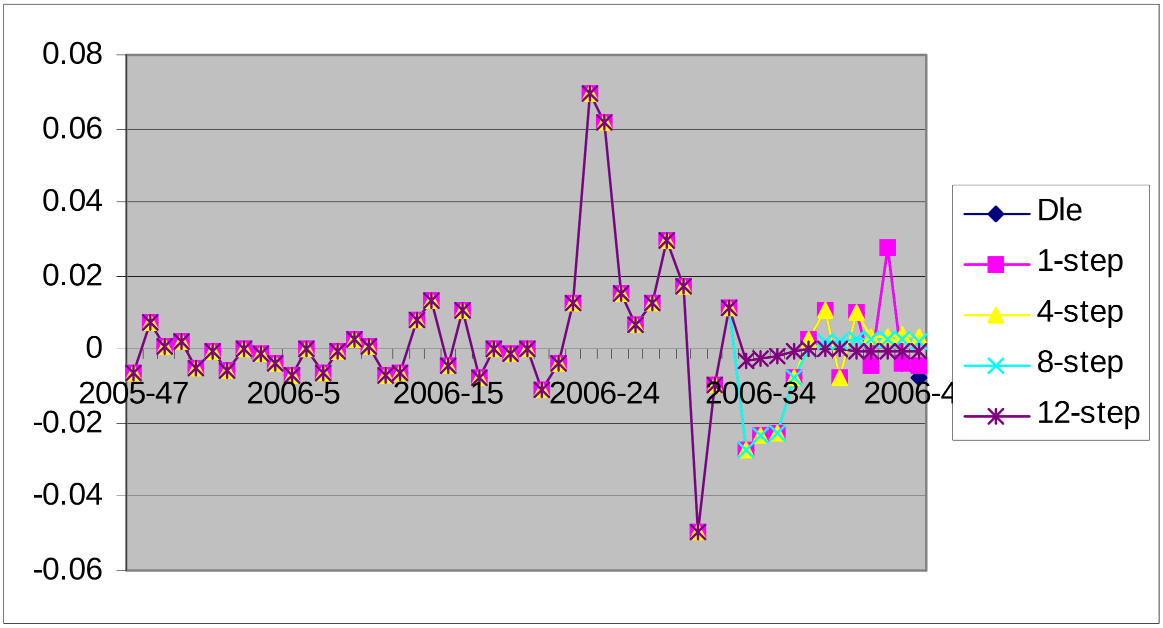

Figure 1:

changes in intercept term and variance, VECM with a constant term in the error correction equation, respectively.

Figure 2 demonstrates the congruent model chosen by comparing MAPE statistics of dynamic forecasting. 1-step, 4-step and 12-step predictions represent VECM with a constant term in the error correction equation, and 8-step prediction demonstrates MSVECM with a constant term in the error correction equation and with regime changes in intercept term, variance and coefficients.

For Turkish Treasury domestic bond return, the appropriate models gathered from the comparison among the RMSE statistics and among the MAPE statistics of dynamic forecasting results are shown in Figure 3 and 4 respectively, for all 1-step, 4-step, 8-step and 12-step predictions.

Figure 3 displays the appropriate model chosen by comparing RMSE statistics of dynamic

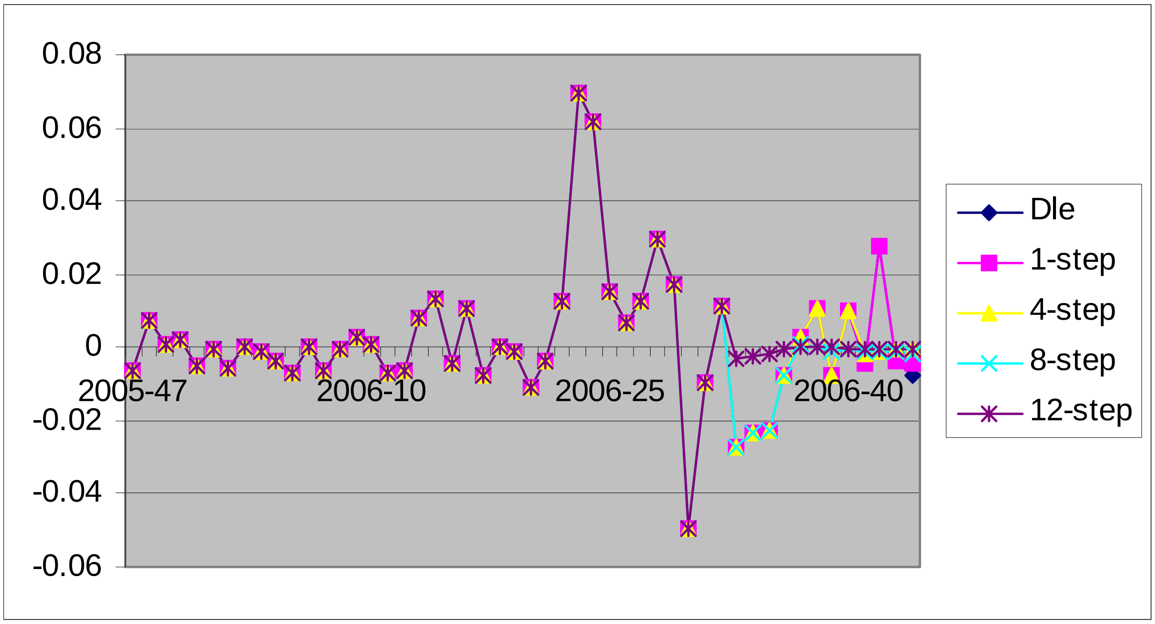

Figure 2:

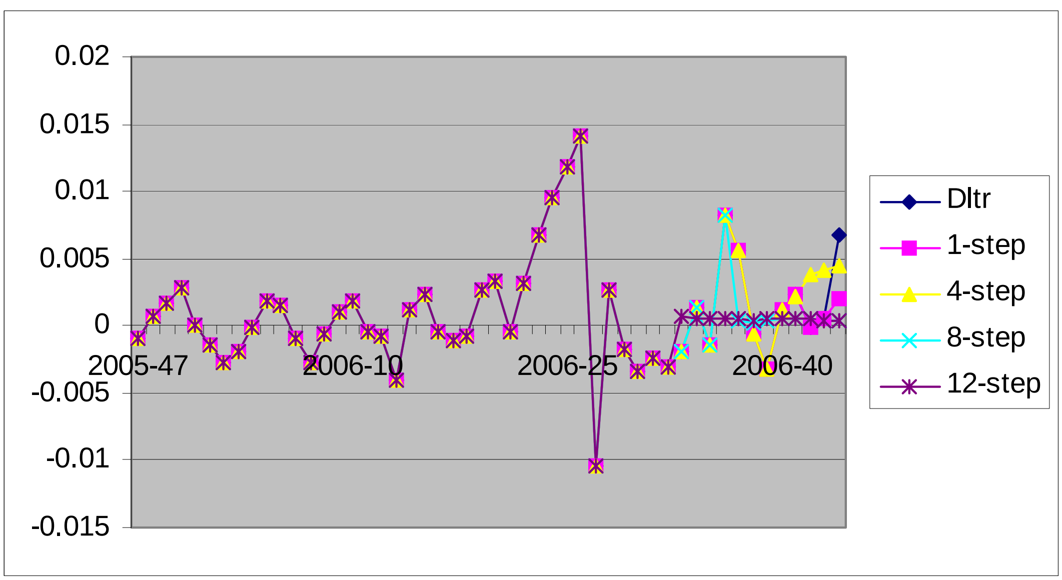

Figure 3:

forecasting. 1-step, 4-step, 8-step and 12-step predictions represent MSVECM with a constant term in the error correction term with regime changes in the intercept term, MSVECM without a constant term in the error correction equation and with regime switches in the intercept variance and coefficients, MSVECM with a constant term in the error correction equation and with regime changes in the intercept and variance, and MSVECM with a constant term in the error correction equation and with regime switches in the intercept and variance, respectively.

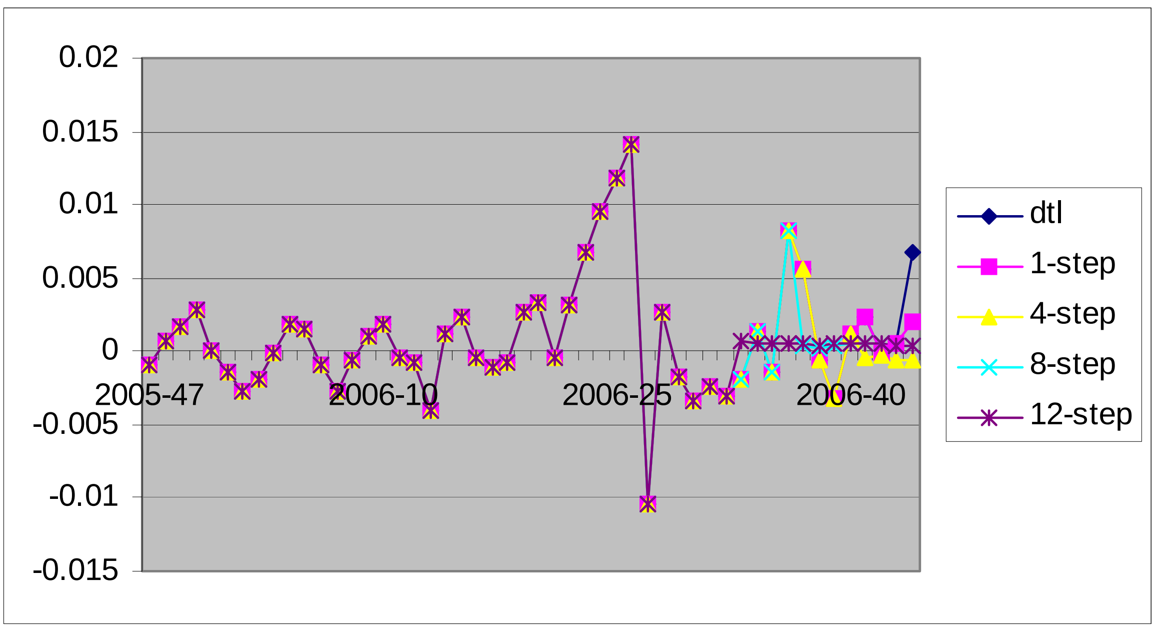

Figure 4:

Figure 4 illustrates the proper model chosen by comparing MAPE statistics of dynamic forecasting. 1-step, 4-step, 8-step and 12-step predictions represents MSVECM with a constant term in the error correction term and with regime changes in the intercept term, MSVAR with regime switches in the intercept and variance, MSVECM without a constant term in the error correction equation and with regime changes in the intercept and variance, and MSVECM without a constant term in the error correction equation and with regime switches in the intercept and variance, respectively.

For Turkish Treasury euro bond return, the proper models obtained from the comparison among the RMSE statistics and among the MAPE statistics of dynamic forecasting results are demonstrated in Figure 5 and Figure 6 respectively for all step predictions.

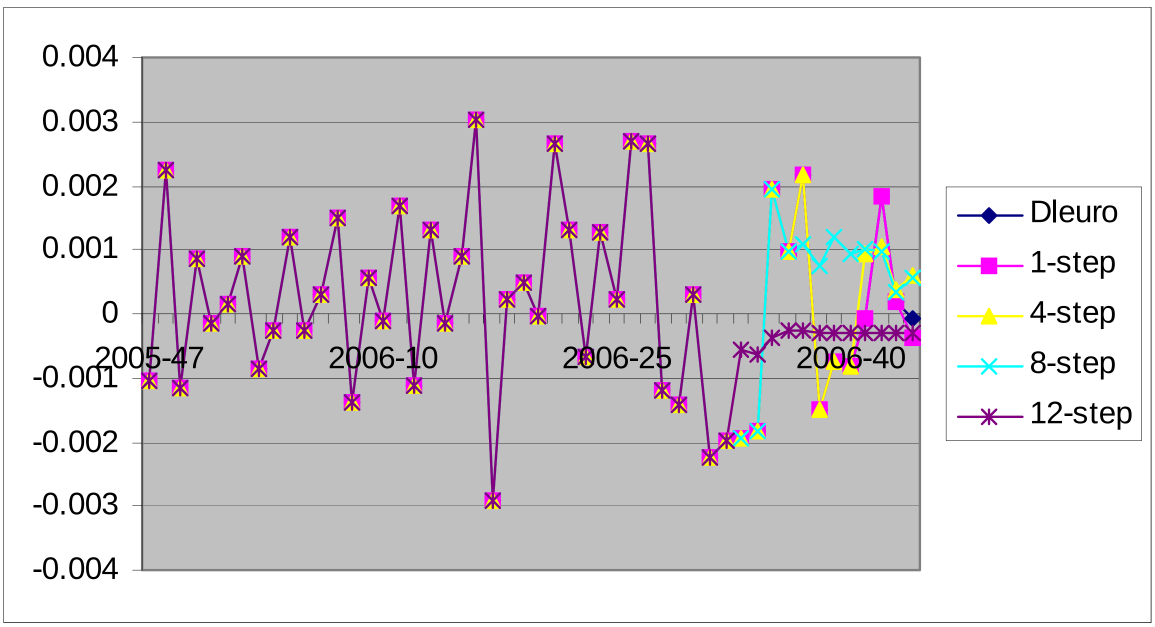

Figure 5:

Figure 5 demonstrates the congruent model chosen by comparing RMSE statistics of dynamic forecasting. 1-step, 4-step, 8-step and 12-step predictions represent MSVAR with regime switches in intercept, variance, MSVECM without a constant term in the error correction equation and with a regime changes in intercept, variance and coefficients, MSVECM with a constant term in the error correction equation and with regime changes in the intercept, variance and coefficients, MSVAR with regime changes in intercept and variance, respectively.

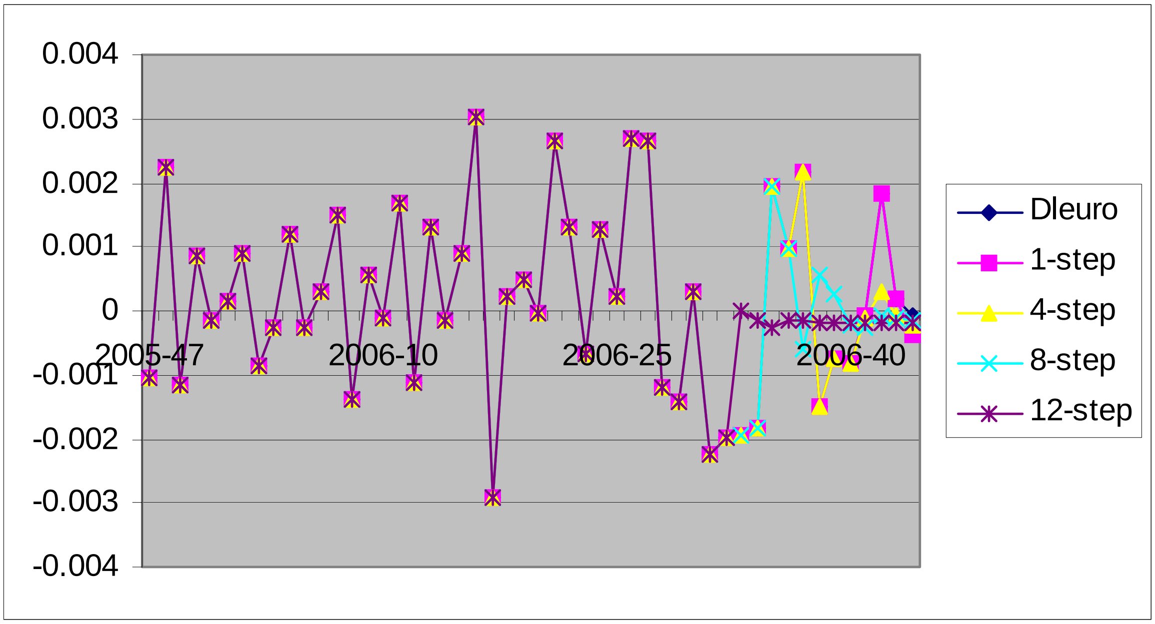

Figure 6:

Figure 6 displays the appropriate model chosen by comparing MAPE statistics of dynamic forecasting. 1-step predictions represents MSVAR with regime changes in intercept and variance and 4-step, 8-step and 12-step predictions represent MSVAR model with regime switches in intercept term.

Furthermore, for static forecasting, we conclude that exchange rate has a linear tendency in the 4-step and 8-step predictions. For that variable, the appropriate model obtained from the comparison among the RMSE statistics and among the MAPE statistics of static forecasting results are presented in Figure 7 and Figure 8, respectively, for all step predictions.

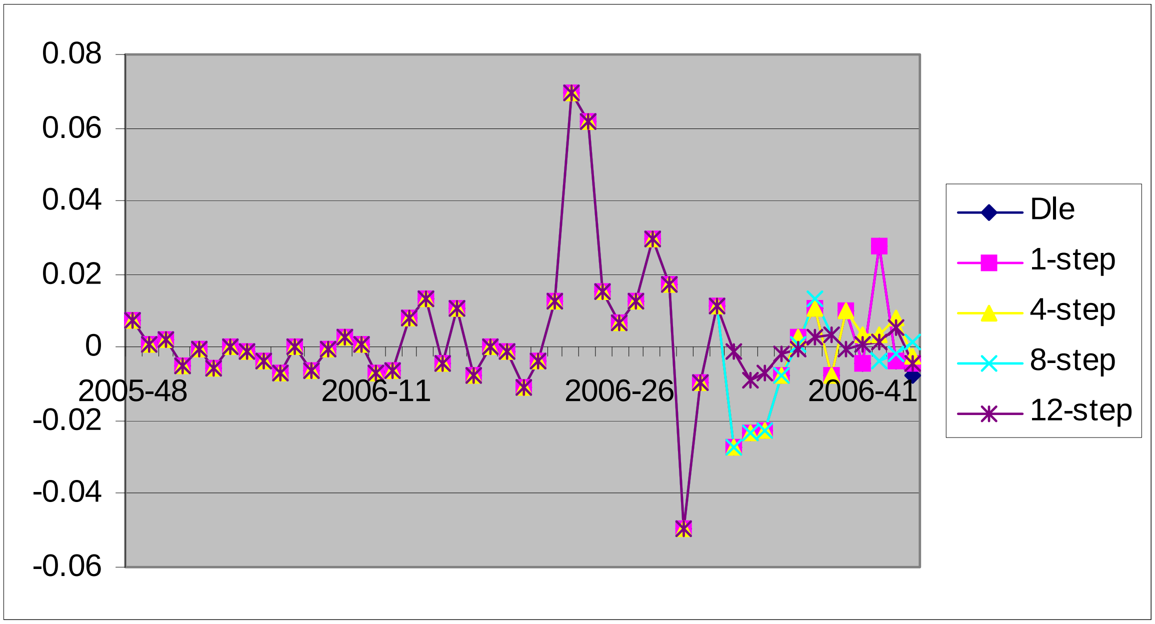

Figure 7:

Figure 7 illustrates the proper model chosen by comparing RMSE statistics of static forecasting. 1-step, 4-step, 8-step and 12-step predictions represent MSVECM with a constant term in the error correction term and with regime changes in the intercept term, VECM without a constant term in the error correction equation, VAR(2) Model, and MSVECM with a constant term in the error correction equation and with regime switches in the intercept term, respectively.

Figure 8 demonstrates the congruent model chosen by comparing MAPE statistics of static forecasting. 1-step, 4-step, 8-step and 12-step predictions represent MSVECM with a constant term in the error correction term and with regime changes in the intercept term and VAR(2) Model respectively. 8-step and 12-step predictions represent MSVAR Model with regime changes in the intercept, variance and coefficients.

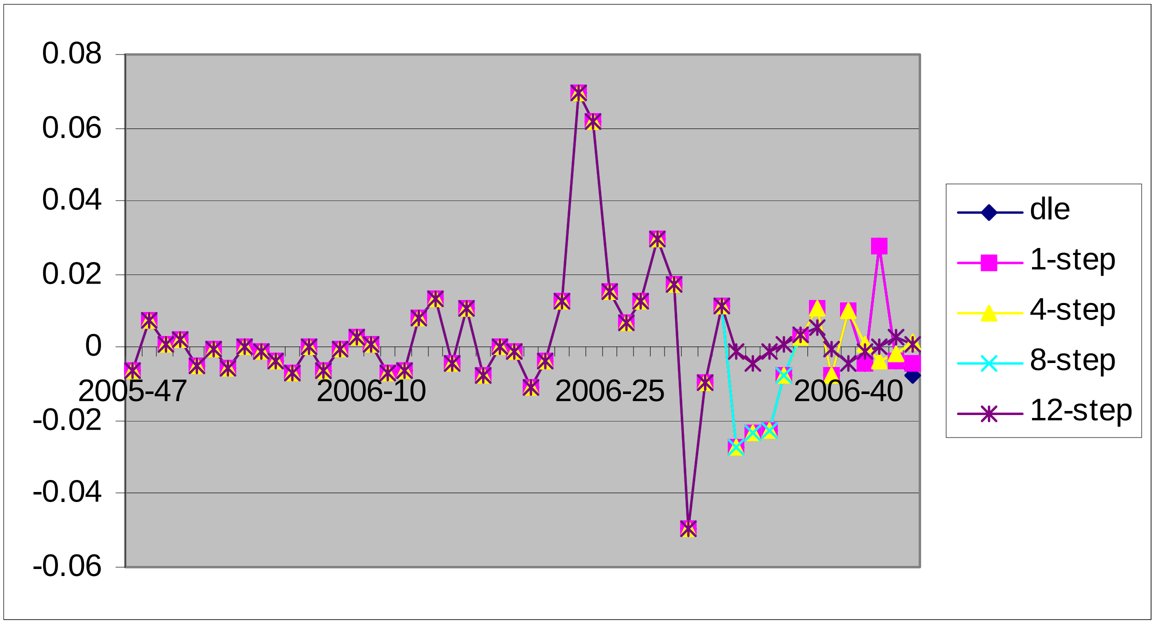

Figure 8:

Turkish Treasury Domestic bond return supports nonlinear model in all step predictions for static forecasting. For that variable, the congruent model provided from the comparison among the RMSE statistics and among the MAPE statistics of static forecasting results are demonstrated in Figure 9 and Figure 10, respectively, for all step predictions.

Figure 9 displays the appropriate model chosen by comparing RMSE statistics of static forecasting. 1-step predictions represents the appropriate models MSVECM without a constant term in the error correction equation and regime changes in the intercept term and 4-step, 8-step and 12-step predictions demonstrate MSVECM without a constant term in the error correction equation and with regime changes in intercept term, variance and coefficients.

Figure 10 illustrates the proper model chosen by comparing MAPE statistics of static forecasting. 1-step prediction represents the appropriate models MSVECM without a con-

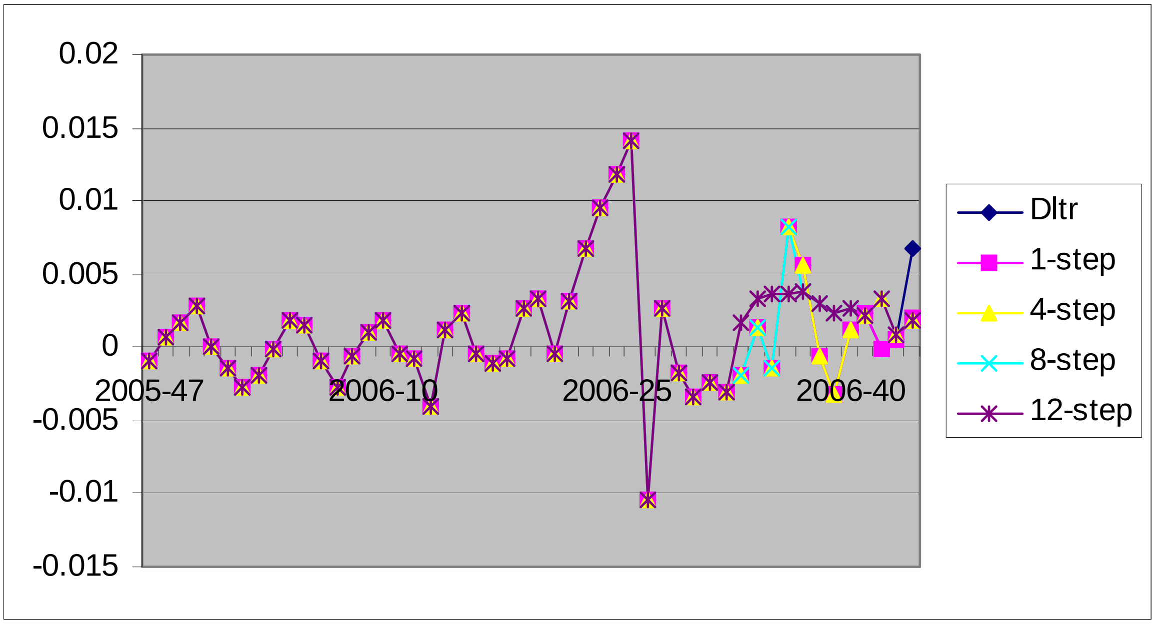

Figure 9:

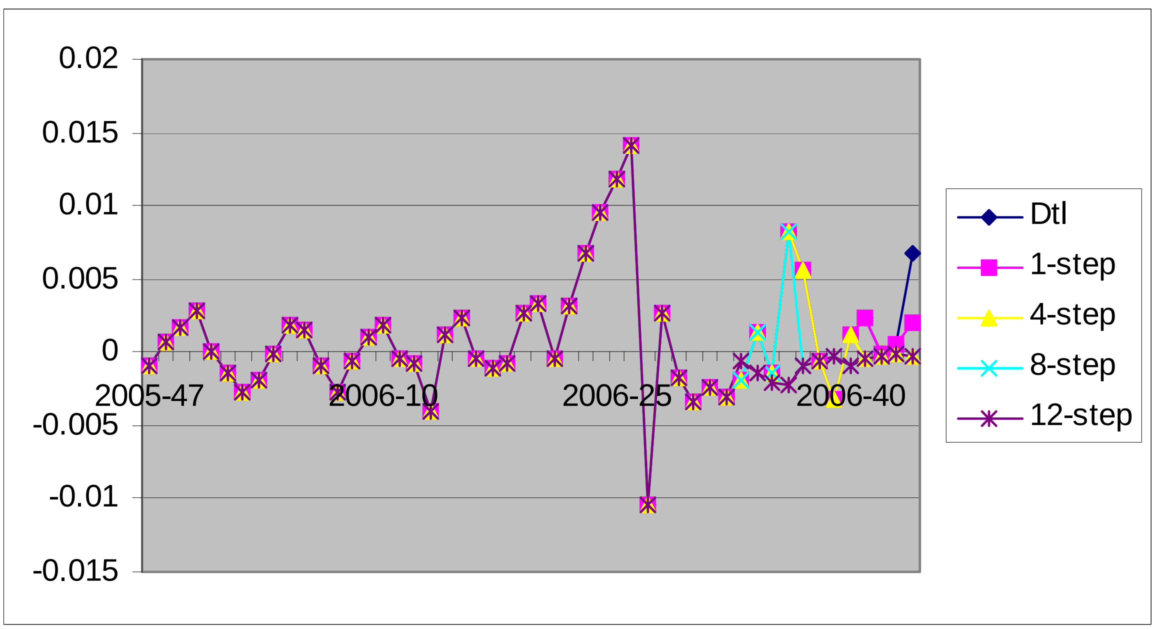

Figure 10:

stant term in the error correction equation and with regime changes in the intercept term and 4-step, 8-step and 12-step predictions demonstrates MSVECM without a constant term in the error correction equation and with regime changes in intercept term, variance.

Turkish Treasury euro bond return move linearly in the 4-step and 12-step predictions. For that variable, the proper model ensured by the comparison among the RMSE statistics and among the MAPE statistics of static forecasting results are illustrated in Figure 11 and Figure 12, respectively, for all step predictions.

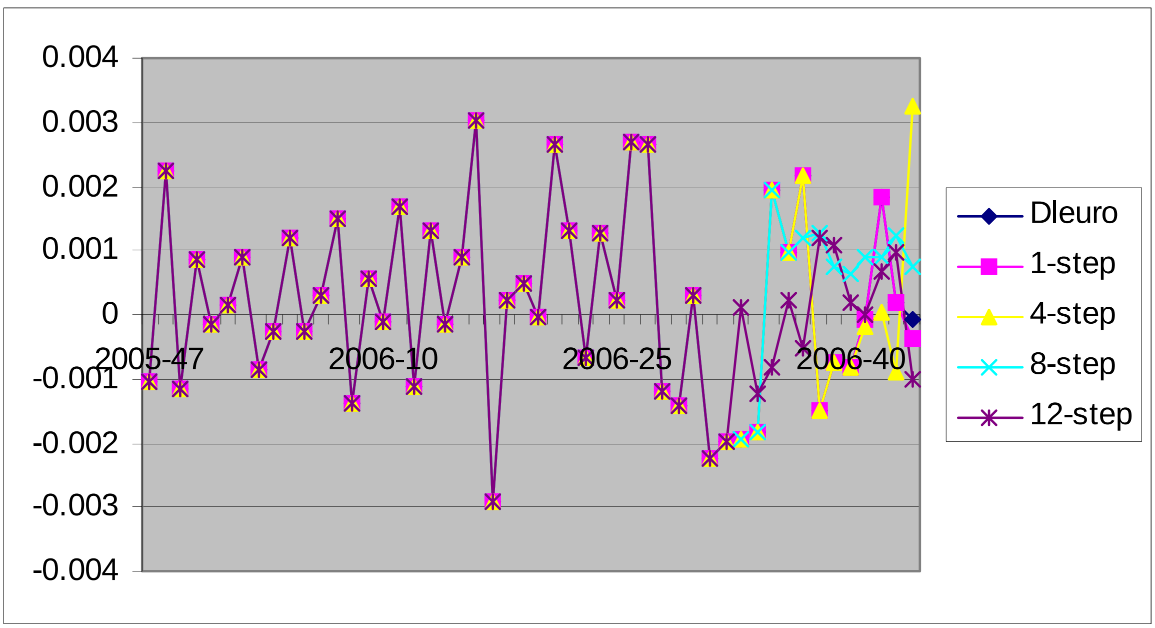

Figure 11:

Figure 11 demonstrates the appropriate model chosen by comparing RMSE statistics of static forecasting. 1-step predictions represents MSVAR with regime changes in the intercept term and variance, 4-step and 12-step predictions demonstrate VAR Model and 8-step predictions shows MSVECM without a constant term and with regime changes in intercept term and variance.

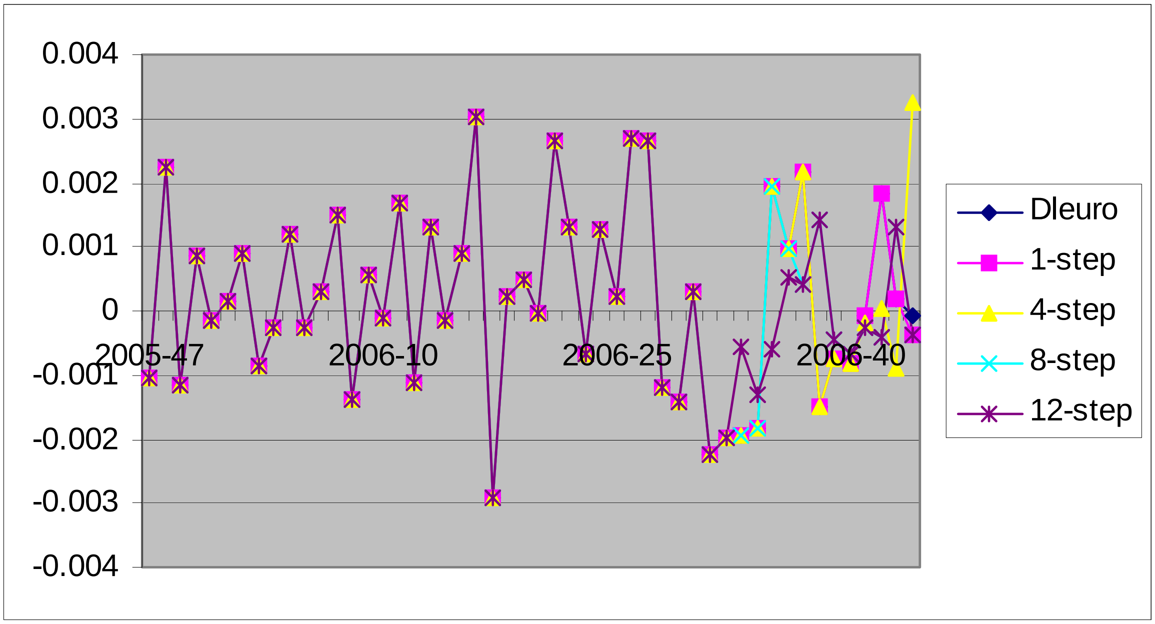

Figure 12:

Figure 12 displays the congruent model chosen by comparing MAPE statistics of static forecasting. 1-step, 8-step and 12-step predictions represent MSVAR with regime changes in the intercept term and variance, 4-step prediction demonstrates VAR(2) Model.

While a great many of the variables has a tendency towards non-linear model, there are some that are in favor of linear model and this linear movement should not be taken into consideration.

After the comparison of error statistics of forecasting results that is based on variables and steps prediction, we complete our analysis by examining linearity tests. For all models with three types of regime changes for each, likelihood ratio (LR) linearity test statistics support the non-linear model. Normally, LR test is two times the difference of logaritmic likelihood of linear and nonlinear models but; in large samples, κ^2 (p) distribution can also be used where p is the number of restrictions in H_0. Instead of this distribution, in order to approximate LR test, critical value of κ^2 (p+q) distribution can be evaluated which was developed by Ang and Bekaert (1998). In this case p represents the number of restricted parameters and q represents the number of nuisance parameters. As a result, we observe that the results with p and p+q degrees of freedom strongly reject the linearity hypothesis. Furthermore, the Davies (1977) upper bound test also supports the non-linear model. All results are displayed in Table (21).

We extend our analysis by checking model selection criteria . Three model selection criteria as Akaike Information Criteria (AIC), Schwarz Criteria (SC) and Hannan Quinn Criteria (HQC) are illustrated in Table(22). For all non linear models with three types of regime changes for each, we display all information criteria results in the 2nd, 3rd and 4th column. Moreover, 5th, 6th and 7th column give information criteria results of linear model that corresponds to non linear model. After we compare linear and non linear models, we observe that non linear models, MSI-VAR, MSIH-VECM with a constant term in the error correction equation and MSIH-VECM without a constant term in the error correction equation, give better results than the corresponding linear models; VAR, VECM with a constant term in the cointegration equation and VECM without a constant term in the cointegration equation. These results are presented in 3 types of regime changes; changes in intercept term, changes in intercept term and variance, changes in intercept term, variance and coefficients. If a comparison is done among the information criteria of the regime changes, we reach the result that regime changes in intercept term and variance give better results than regime changes in intercept, variance and coefficients. Additionally, the model with changes in all coefficients gives better results than with regime changes in intercept term. Finally, we compare the three models. MSIH-VECM with a constant term and without a constant term in the error correction equation give the same results and both model give better results than MSIH-VAR model. The result stated here are valid for all three information criteria: AIC, HQ criteria and SC.

4.3 Long-run Analysis

We will concentrate on the model selection by comparing forecasting accuracy of the model and by focusing on the related linearity tests results. Thus, we only use forecasting result of the model, instead of the model itself. We first consider long run dynamics of our models and demonstrate error statistics of ex ante and ex post forecasting results of the the linear and non-linear models. We use root mean square error (RMSE) and mean absolute percentage error(MAPE) as our error statistics of forcasting results. Afterwards, we follow our study by comparing the error statistics of the forecasting results of all models. Linearity test results are then checked.

4.3.1 Model Setting of long run data

In the short run, we dealt with bonds with maturities 90 days. For long run data, we now focus on the data with maturities 360 days. The same procedure as in short run is followed here. As we mentioned in the subsection one, we handle first difference of weekly data from week 2 of 2000 to week 43 of 2006. In the data analysis, we found out that SC gave second lag of the system. Also, as in the short run case, we analyze the effect of constant term on the spread; therefore, this constant term is included in the error correction equation but, not exist in the main equation. So, we apply the data to equation (2) with p=2, m=1 and no constant term. Since we use error term of forecasting results as our model selection tool, we display forecasting results of the models. Error statistics of static and dynamic forecasting results of VAR model with 1-step, 4-step ,8 -step, 12-step forecasting period are illustrated in Table (23).

Table (24) displays the results of cointegration tests. Similar to the case in the short run, we have two cointegration relations for both of the cointegration equations; with a constant term and without a constant. To see how the risk free bonds are exposed to the country risk, we take the spread between domestic Treasury bond return and US Treasury bond return as the first cointegration relation and the spread between euro-bond return and US Treasury bond return as the second cointegration relation. Both cointegration equations, displayed below with a constant term and without constant, are also analyzed.

Cointegration equation with a constant term:

$$ltl_t - lus_t = -0.18705 + \xi_{1,t+1}$$

$$leuro_t - lus_t = -0.016554 + \xi_{2,t+1}$$

Cointegration equation without a constant term:

$$ltl_t - lus_t = \xi_{1,t+1}$$

$$leuro_t - lus_t = \xi_{2,t+1}$$

We first study on the VECM with a constant term in cointegration relation. The other VEC model, VECM without a constant term in the error correction equation, is also analyzed. Table (25) and Table(26) represent the error statistics of forecasting results of VECM with a constant term in the cointegration equation and VECM with no constant term in the cointegration equation, respectively. Similar to Table(23), Table (25) and Table(26) display 1-step, 4-step, 8-step and 12-step ex ante and ex post forecasting results.

We will continue on our analysis by focusing on the state dependency of variables and error terms as in short run. Since we select the model by comparing forecasting accuracy of the models, we represent static and dynamic forecasting results of the models. We focus on the regime switches in intercept term for VAR model and for both VEC models. We reach MSI- VAR model for VAR model, and MSI-VECM for both VEC models. Error statistics of forecasting results of MSI-VAR model are presented in Table(27) with1-step, 4-step, 8 step and 12-step both in ex ante and ex post forecasting. Also, table(28) and table(29) illustrate error statistics of forecasting of MSI-VECM with a constant term in cointegration relation and MSI-VECM model without a constant term in error correction term respectively. In that Table(28) and (29), static and dynamic forecasting results and all step prediction are demonstrated as in Table(27).

Then, our study is sustained by investigating regime changes in the intercept term and variance. MSIH- VAR model and MSIH- VECM model for both VEC models are obtained. In Table(30), we observe error statistic of the forecasting results of MSIH-VAR model with 1-step. 4-step, 8-step and 12-step prediction both in ex ante and ex post. Table(31) and Table(32) represent error statistics of forecasting results of MSIH-VECM with a constant term in the error correction term and MSIH-VECM without a constant term in the error correction term,respectively, with all step predictions. These illustration are both for static and dynamic forecasting

Finally, we extend our analysis by examining the state changes in intercept term, variance and all coefficients in the model. Table(33) represents error statistics of static and dynamic forecasting results of MSIH-VAR model with 1-step, 4-step, 8-step and 12-step predictions. Error statistics of static and dynamic forecasting results of MSIH-VECM with a constant term in error correction term and without a constant term in error correction term with all step of prediction can be seen in Table(34) and in Table(35) respectively.

4.3.2 Model comparision of long run data

First of all, the appropriate model for the variables is determined by measuring the smallest error term of static and dynamic forecasting results. Then, for evaluation process, we take the linearity test results and model selection criteria test results of the models.

Initially, the RMSE and MAPE statistics of forecasting results of the models are studied. We demonstrate the efficient model for 1-step, 4-step, 8-step and 12-step prediction in Table (36), both for static and dynamic forecasting. For dynamic forecasting, we deduce that all variables are proper for nonlinear models in all step predictions. For exchange rate variable, the congruent model obtained from the comparison among the RMSE and among the MAPE statistics of dynamic forecasting results are displayed in Figure 13 and Figure 14 respectively, for all 1-step, 4-step, 8- step and 12-step predictions.

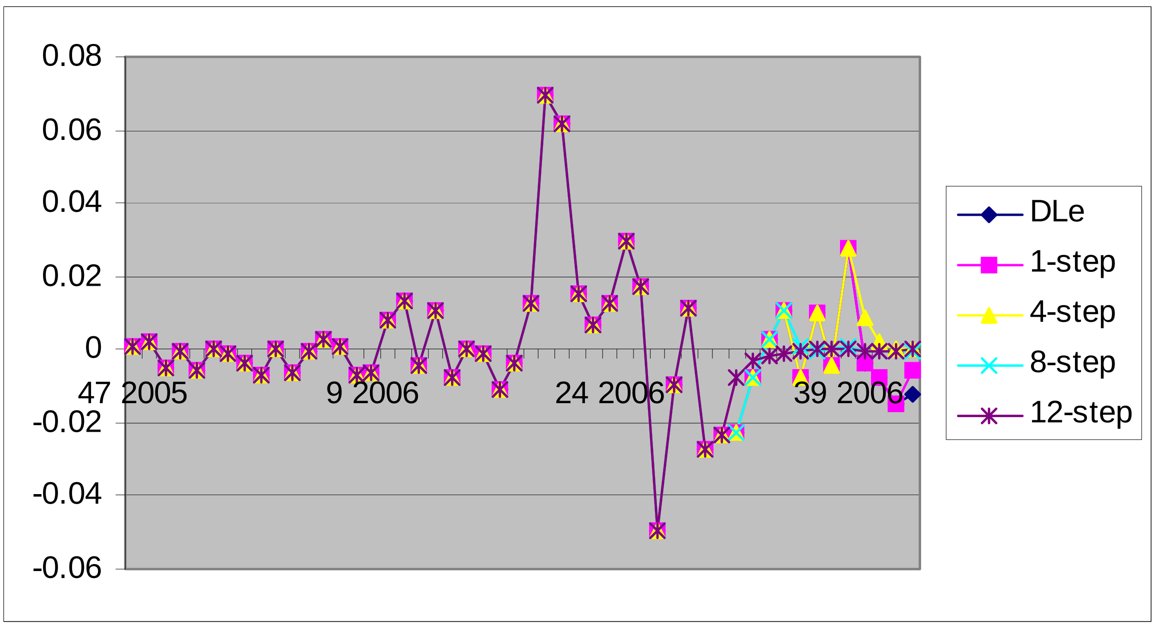

Figure 13:

Figure 13 illustrates the proper model chosen by comparing RMSE statistics of dynamic forecasting. 1-step and 12-step predictions represent MSVECM with a constant term in the error correction equation and with regime changes in the intercept, variance and coefficients, 4-step prediction presents MSVAR Model with regime changes in the intercept and variance, and 8-step prediction demonstrates MSVAR with regime changes in intercept term, variance and coefficients.

Figure 14 demonstrates the congruent model chosen by comparing MAPE statistics of

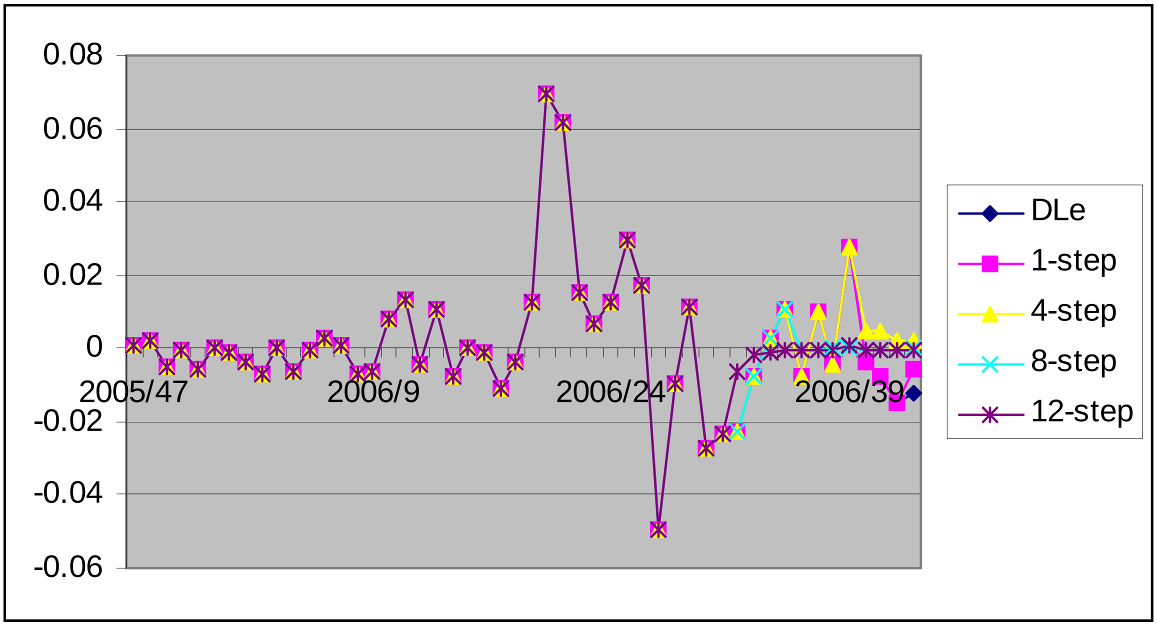

Figure 14:

dynamic forecasting. 1-step and 8-step predictions represent MSVECM with a constant term in the error correction equation and with regime changes in intercept, variance and coefficients, 4-step prediction illustrates MSVAR with regime changes in the intercept term, 12-step prediction displays MSVAR with regime changes in intercept term, variance and coefficients.

For Turkish Treasury bond return, the appropriate model gathered from the comparison among the RMSE statistics and among the MAPE statistics of dynamic forecasting results are shown in Figure 15 and 16 respectively, for all 1-step, 4-step, 8-step and 12-step predictions.

Figure 15 displays the appropriate model chosen by comparing RMSE statistics of dynamic forecasting. 1-step, 4-step, 8-step and 12-step predictions represent MSVECM without

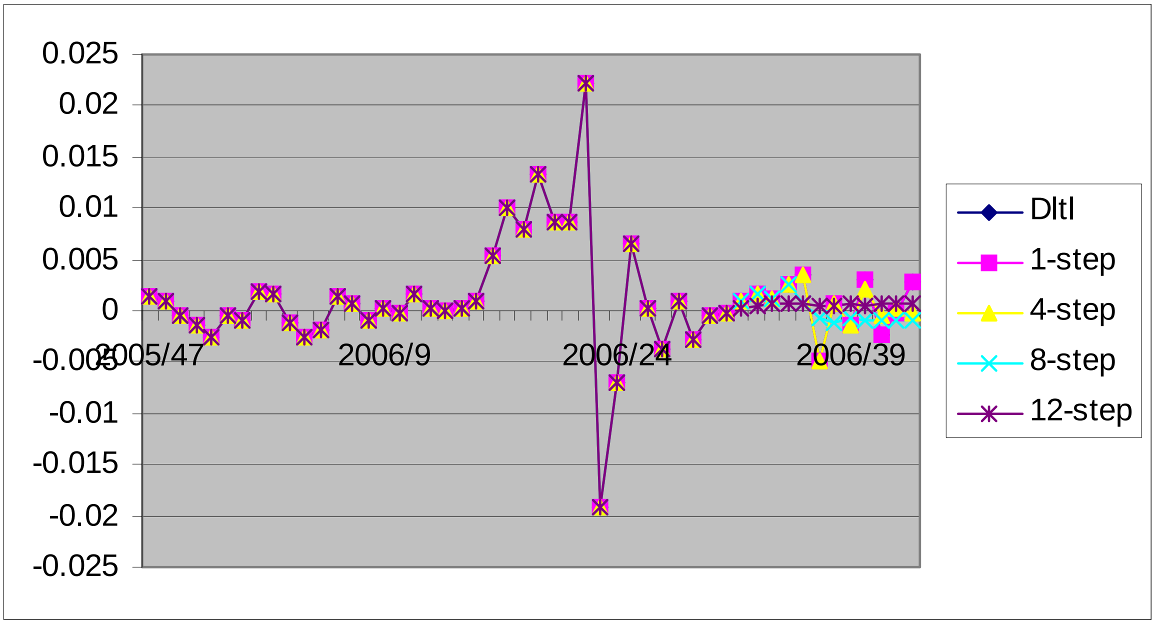

Figure 15:

a constant term in the error correction equation and with regime changes in the intercept term, MSVAR Model with regime changes in the intercept term, MSVAR with regime changes in intercept term, variance and coefficients and MSVECM without a constant term in the error correction equation and with regime changes in the intercept and variance, respectively.

Figure 16 illustrates the proper model chosen by comparing MAPE statistics of dynamic forecasting. 1-step, 4-step, 8-step and 12-step predictions represent MSVECM without a constant term in the error correction equation and with regime changes in the intercept term, MSVAR Model with regime changes in the intercept term, MSVAR with regime changes in intercept term, and MSVECM without a constant term in the error correction equation and with regime changes in the intercept and variance, respectively.

For Turkish Treasury euro bond return, the proper model provided from the com-

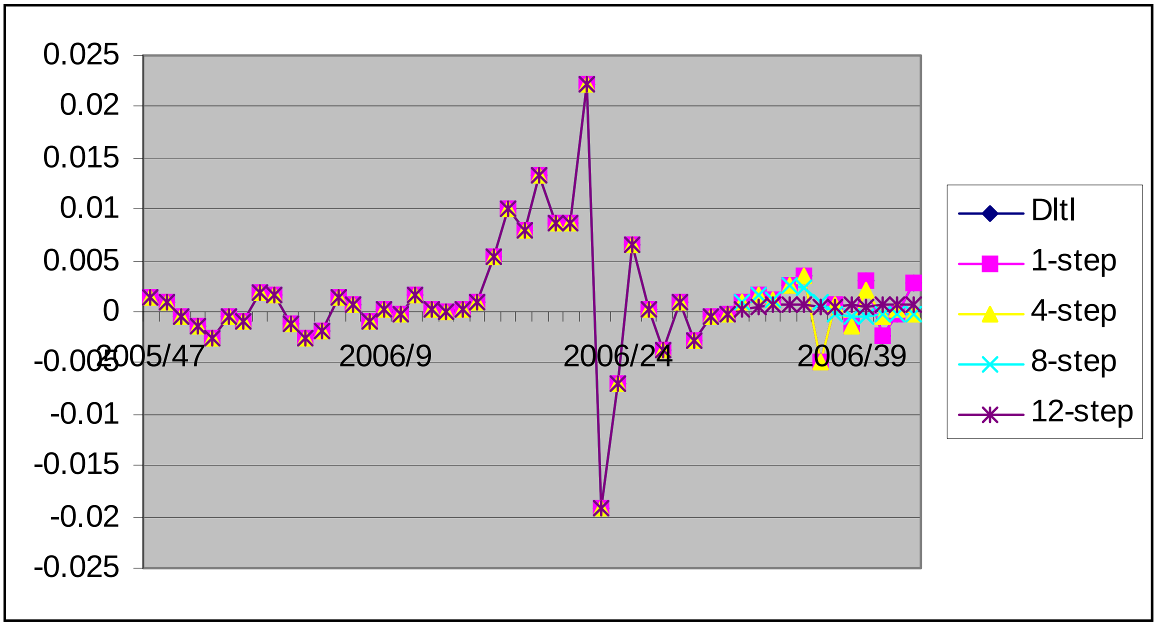

Figure 16:

parison among the RMSE statistics and among the MAPE statistics of dynamic forecasting results are demonstrated in Figure 17 and Figure 18 respectively for all step predictions.

Figure 17 demonstrates the congruent model chosen by comparing RMSE statistics of dynamic forecasting. 1-step predictions represents MSVECM with a constant term in the error correction equation and with regime changes in the intercept, variance and coefficients, 4-step and 8-step predictions present MSVAR Model with regime changes in the intercept and variance, 12-step predictions displays MSVAR with regime changes in intercept term, variance.

Figure 18 displays the appropriate model chosen by comparing MAPE statistics of dynamic forecasting. 1-step and 12-step predictions represent MSVECM with a constant term in the error correction equation and with regime changes in the intercept, variance and coef-

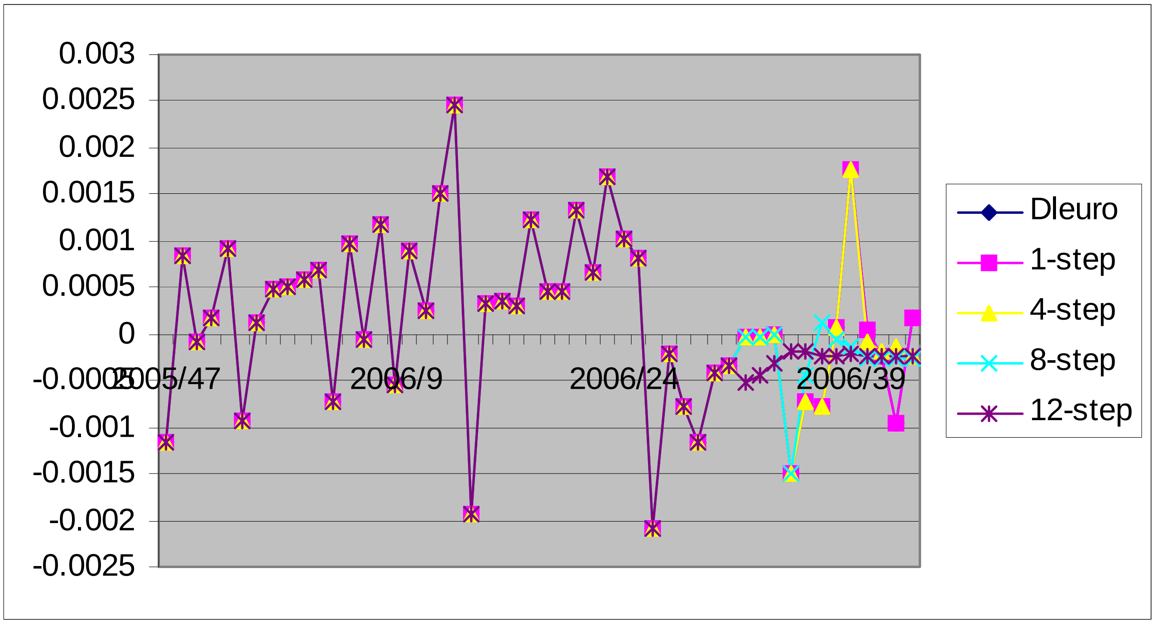

Figure 17:

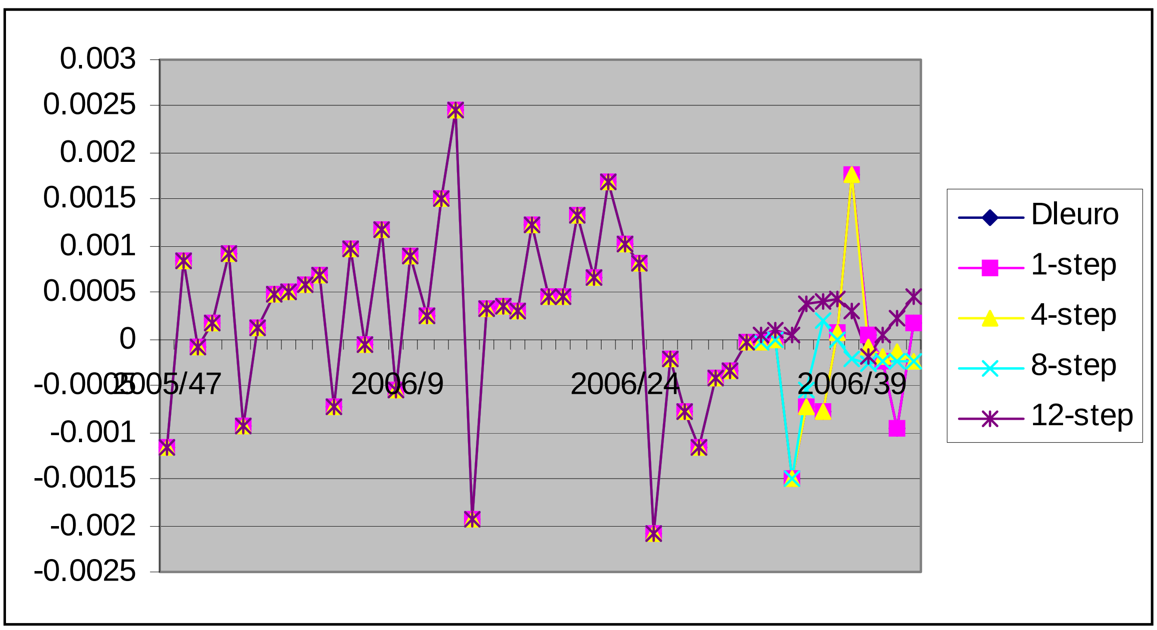

Figure 18:

ficients, 4-step prediction presents MSVAR Model with regime changes in intercept, variance and coefficients and 8-step predictions present MSVAR Model with regime changes in the intercept and variance.

Moreover, for static forecasting, exchange rate variable move linearly in 8-step and 12-step predictions. For that variable, the appropriate model obtained from the comparison among the RMSE statistics and among the MAPE statistics of static forecasting results are presented in Figure 19 and Figure 20, respectively, for all step predictions.

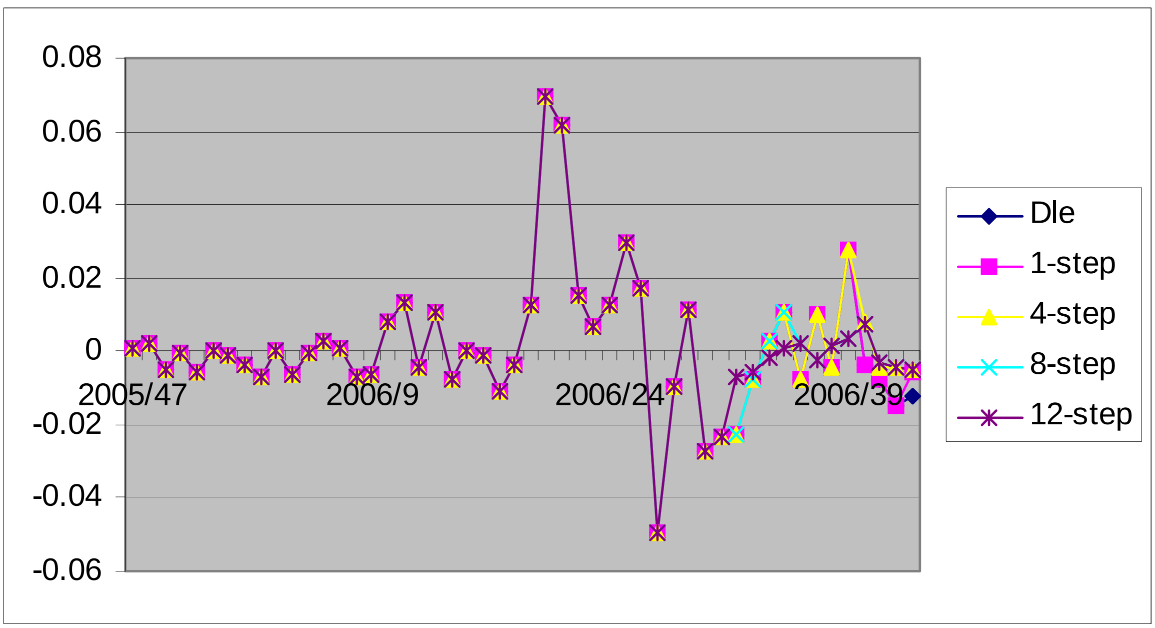

Figure 19:

Figure 19 illustrates the congruent model chosen by comparing RMSE statistics of static forecasting. 1-step represents MSVECM with a constant term in the error correction equation an with regime switches in intercept, variance and coefficients, 4-step presents MSVECM without a constant term in the error correction equation and with regime changes in intercept and 8-step and 12 step display VAR(2) Model.

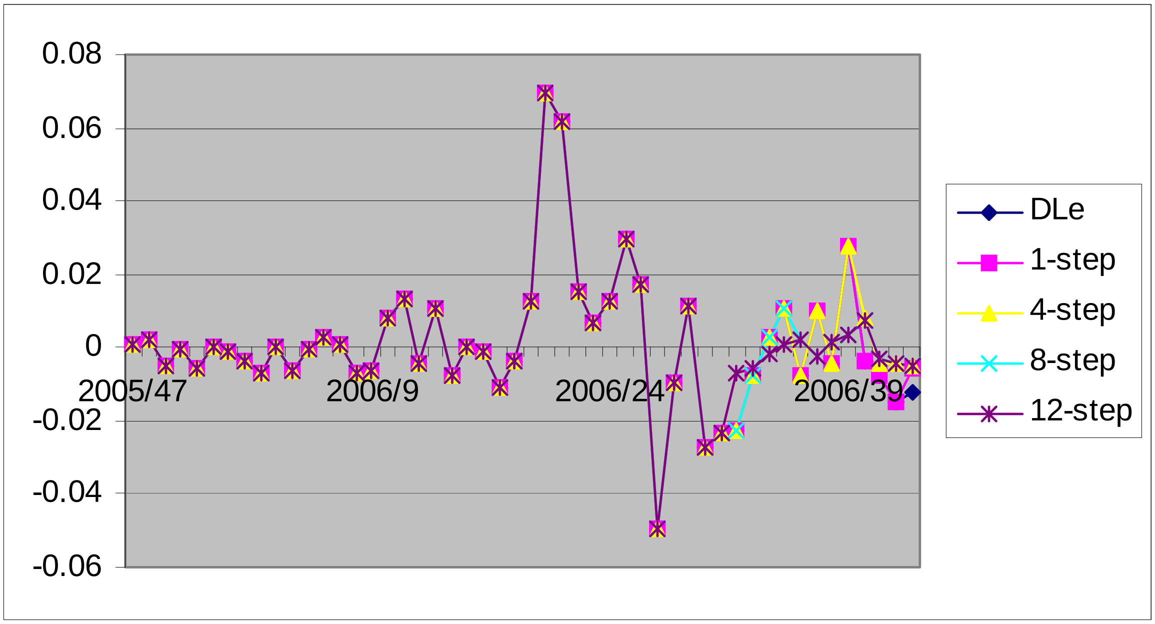

Figure 20:

Figure 20 demonstrates the congruent model chosen by comparing MAPE statistics of static forecasting. 1-step represents MSVECM with a constant term in the error correction equation and with regime changes in intercept, variance and coefficients, 4-step presents MSVECM with a constant term in the error correction equation and with regime switches in intercept and 8-step and 12 step display VAR(2) Model.

Turkish Treasury domestic bond return move linearly in the 4-step and 12-step predictions. For that variable, the congruent model provided from the comparison among the RMSE statistics and among the MAPE statistics of static forecasting results are presented in Figure 21 and Figure 22, respectively, for all step predictions.

Figure 21 displays the appropriate model chosen by comparing RMSE statistics of static

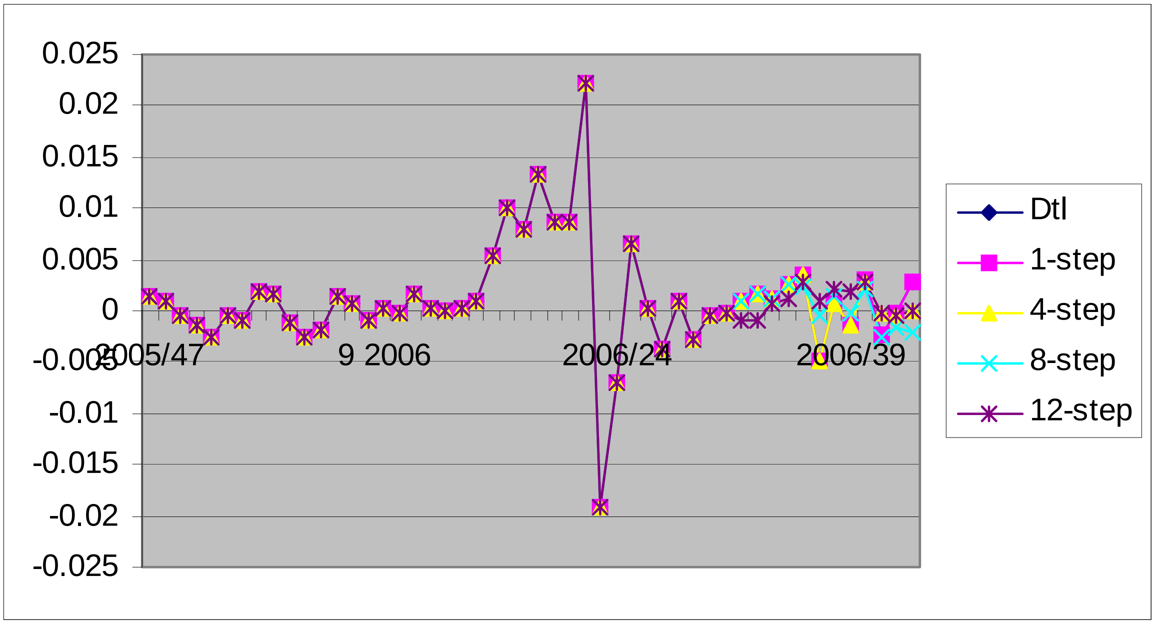

Figure 21:

forecasting. 1-step represents MSVECM with a constant term in the error correction equation an with regime switches in intercept, 4-step and 12-step present VECM without a constant term in the error correction equation and 8-step MSVAR Model with regime changes in intercept term.

Figure 22 illustrates the proper model chosen by comparing MAPE statistics of static forecasting. 1-step, 4-step, 8-step and 12-step represent MSVECM with a constant term in the error correction equation and with regime switches in intercept, VECM without a constant term in the error correction equation, VAR(2) Model, MSVECM without a constant term in the error correction equation and with regime changes in intercept, variance and coefficients.

For Turkish Treasury euro bond return has a nonlinear movement for all step prediction, the proper model gathered from the comparison among the RMSE statistics and among

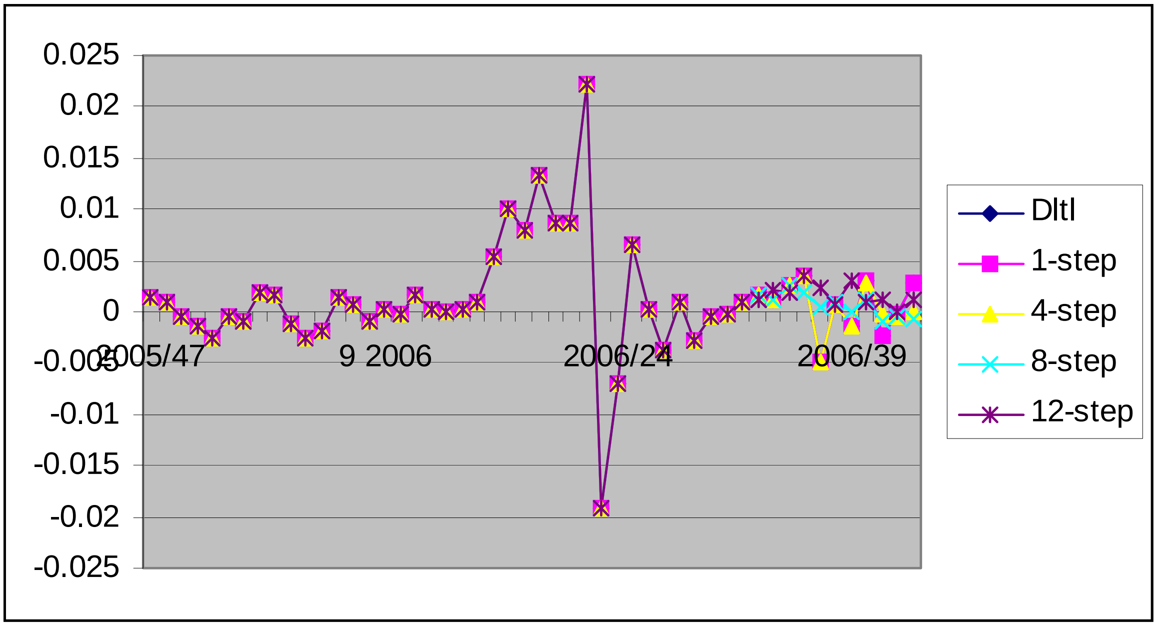

Figure 22:

the MAPE statistics of static forecasting results are presented in Figure 23 and Figure 24, respectively, for all step predictions.

Figure 23 displays the appropriate model chosen by comparing RMSE statistics of static forecasting. 1-step, 4-step, 8-step and 12-step represent MSVECM with a constant term in the error correction equation and with regime switches in intercept, variance and coefficients.

Figure 24 demonstrates the appropriate model chosen by comparing MAPE statistics of static forecasting. 1-step and 12-step represent MSVECM with a constant term in the error correction equation and with regime switches in intercept, variance and coefficients and 4-step and 8-step display MSVAR Model with regime switches in intercept, variance and coefficients.

Except this linear movements, for static forecasting, all variables follow nonlinear

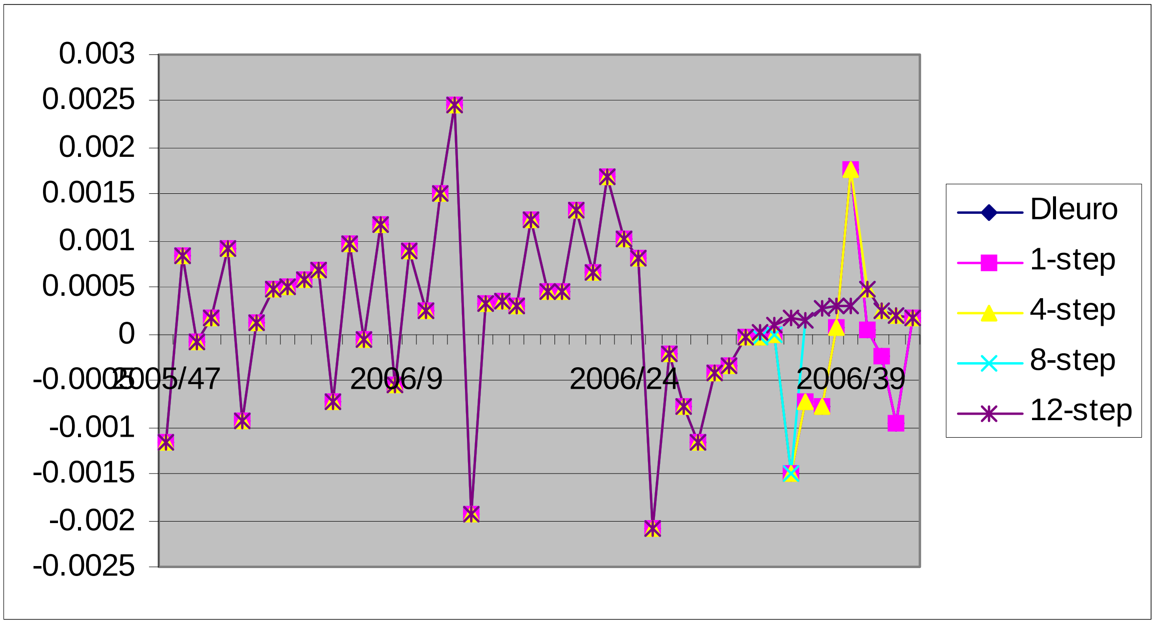

Figure 23:

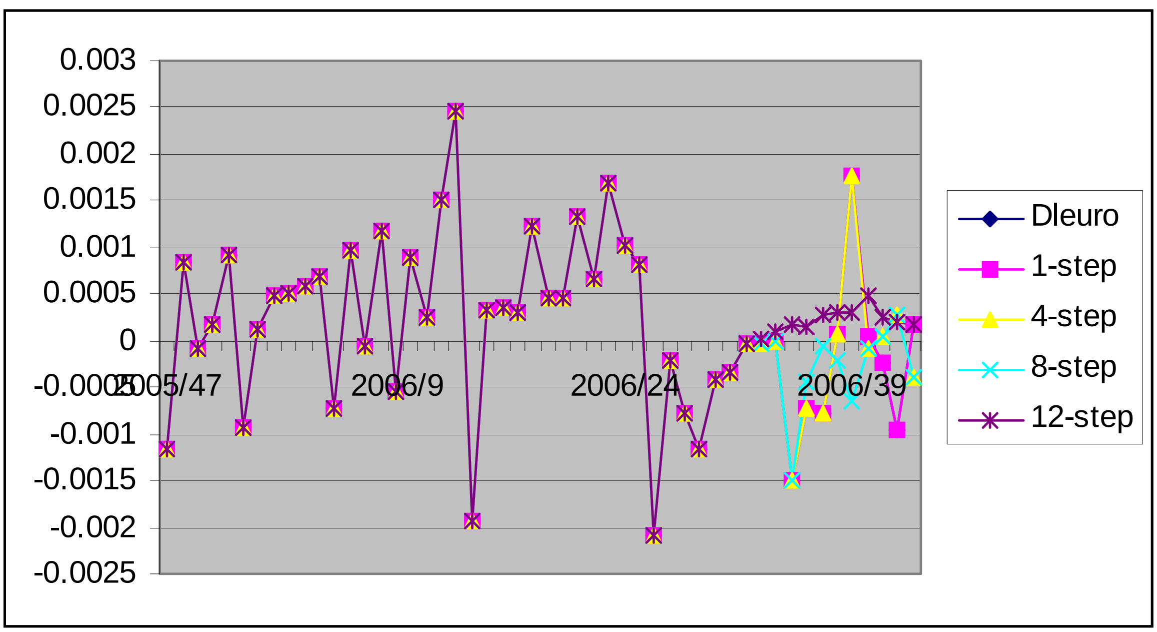

Figure 24:

model in all step predictions. Although, some variables have a tendency to linear models for some step prediction, we notice that in general, test statistics are in favor of non linear models. Thus, we do not emphasize this linear movement.

Then, we accomplish our analysis by examining linearity tests as in short run case. For all models with three types of regime changes for each, likelihood ratio (LR) linearity test statistics support non linear models. Alternative approach to LR test, $\kappa^2(p)$ and $\kappa^2(p+q)$ results reject the linearity hypothesis. Moreover, the Davies (1977) upper bound test is also in favor of non-linear model. All test statistics can be seen in Table (37).

Finally, similar to short run case, we examine all model selection criteria; Akaike Information Criteria (AIC), Schwarz Criteria (SC) and Hannan Quinn Criteria (HQC). Table (38) represents information criteria results of non linear models, MS-VAR, MS-VECM with a constant term in the error correction equation and MS-VECM without a constant term in the error correction equation, and corresponding linear models; VAR, VECM with a constant term in the cointegration equation and VECM without a constant term in the cointegration equation. All three types of regime changes, changes in intercept term, changes in intercept term and variance, changes in intercept term, variance and coefficients, are included in the Table (38). Like in the short run, non linear models produce better results than linear model, for all types of Models with all types of regime changes for each. When comparing these three regime changes, regime switches in intercept, variance and coefficients yield better results than state changes in intercept and variance. Also, regime changes in intercept and variance produce better results than changes in intercept. Moreover, if we compare the models, we get the results that both MS-VECM models give the same results and these yield better results than MS-VAR models. The above evaluation is valid for all information criteria; AIC, HQ criteria, and SC.

5 CONCLUSION

In this study, we provide empirical evidence of sovereign spread and exchange rate by using Turkish data. Our aim is to choose the most appropriate model of the variables; exchange rate, Turkish domestic Treasury bond and Turkish Treasury euro bond. We study both for short run and long run data. In the short run case, we observe by comparing error statistics of forecasting results for both linear and non linear models that variables in general have non linear tendency. Unlike this, in static forecasting, exchange rate and Turkish Treasury Euro bond move linearly for some step predictions. Since static forecasting use the observed values, this linear movements need not to be taken into consideration. Furthermore, we support our analysis by evaluating LR linearity test statistics and information criteria test statistics. Both test results are in favor of non linear models and give similar results to the results of error statistics comparison.

In addition to these, in the long run, the comparison of error statistics of forecasting results yields the similar results as in short run case. Moreover, we apply LR linearity test and information criteria tests which support non linear models. It is observed that both for short run and long run evaluation, the comparisons of error statistics give the appropriate model that includes error correction term. This means that there is a contagion on the US Treasury bond market and Turkish Treasury bond market. Finally, we believe that this contagion on the US Treasury bond market and Turkish Treasury Bond market might be an explanatory variable for some further studies on Turkish Economy. Moreover, as a non linear model, Markov Switching model might be an appropriate tool for modeling exchange rate and Turkish Treasury bond return.

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7 APPENDIX

7.1 APPENDIX l : Time Series Properties Of the Data

7.1.1 Short run Results

Table-1: ADF test results	
I-LEVELS	
variables	LEVEL
le	-2.034311 (0.5800)
leuro	-3.120573 (0.1031)
ltl	-2.649086 (0.2589)
lus	-0.130951 (0.9942)
1% CV	-3.984195
5% CV	-3.422569
10% CV	-3.134162

(II) For the first differences	
variables	I(1)
le	−5.942127 (0.0000)∗
leuro	−15.78599 (0.0000)∗
ltl	−12.60573 (0.0000)∗
lus	−2.575138 (0.0849)<
1% CV	-3.448943
5% CV	-2.869629
10% CV	-2.571148

Notes:

- The rejection of the null hypothesis of unit root at 5 % level is denoted by *

- The rejection of the null hypothesis of unit root at 10 % level is denoted by <

- Probability values are given in the paranthesis

- US treasury bond is significant at 10 % significance level other variables are significant at 5 % significance level

Table-2:PP test Results

(I)- Levels

variable	level
le	-1.926602 (0.6384)
leuro	-2.937818 (0.1519)
ltl	-2.591445 (0.2846)
lus	-0.235326 (0.9921)
% 1 CV	-3.448728

(II)- For the first differences

variable	I(1)
le	-14.91624 (0.0000)*
leuro	-15.99392 (0.0000)*
ltl	-11.67666 (0.0000)*
lus	-18.34191 (0.0000)*
% 1 CV	-3.448728

Notes:

- The rejection of the null hypothesis of unit root at 1 % level is denoted by *

- Probability values are given in the paranthesis

- All I(1) variables are significant at 1 % significance level.

-Bandwidth selection is done by default values. Residual spectral is estimated by Barlett

Kernel Model

Table-3 Model Selection Criteria

Order	SC	HQ	AIC
1	-27.373	-27.534	-27.640
2	-27.546<	-27.814	-27.991
3	-27.450	-27.825<	-28.073
4	-27.279	-27.761	-28.079
5	-27.097	-27.686	-28.076
6	-27.024	-27.720	-28.181<
7	-26.791	-27.594	-28.125
8	-26.597	-27.507	-28.109

Notes: (1) Each VAR is estimated over the sample 3. week of 200 to 44. week of 2006

(2) < operator denotes the chosen lag.

7.1.2 Long run Results

Table-4	**ADF test results**
I-LEVELS	
variables	LEVEL
le	-2.007274 (0.5949)
leuro	-1.750672 (0.7264)
ltl	-2.295355 (0.4349)
lus	-0.601802 (0.9780)
1% CV	-3.984195
5% CV	-3.422569
10% CV	-3.134162

II-For the first differences	
variables	I(1)
le	-5.952900 (0.0000)$*$
leuro	-14.25344 (0.0000)$*$
ltl	-4.048275 (0.0013)$*$
lus	-2.575138 (0.0992)$<$
1% CV	
5% CV	
10% CV	

Notes:

- The rejection of the null hypothesis of unit root at 5 % level is denoted by *

- The rejection of the null hypothesis of unit root at 10 % level is denoted by <

- Probability values are given in the paranthesis

- US treasury bond is significant at 10 % significance level other variables are significant at 5 % significance level

Table-5:	**PP test results**
(I)- Levels	
variable	level
le	-1.903209 (0.6507)
leuro	-2.953904 (0.1470)
ltl	-2.324601 (0.4190)
lus	-0.498342 (0.9833)
% 1 CV	-3.448728

(II)- For the first differences	
variable	I(1)
dle	-14.92233 (0.0000)*
dleuro	-13.88040 (0.0000)*
dltl	-16.63621 (0.0000)*
dlus	-13.80139 (0.0000)*
% 1 CV	-3.448728

Notes:

- The rejection of the null hypothesis of unit root at 1 % level is denoted by *

- Probability values are given in the paranthesis

- All I(1) variables are significant at 1 % significance level.

-Bandwidth selection is done by default values. Residual spectral is estimated by Barlett Kernel Model.

Table-6: Model Selection Criteria

Order	SC	HQ	AIC
1	-28.926	-29.085	-29.191
2	-29.027<	-29.293	-29.470
3	-28.958	-29.331	-29.578
4	-28.811	-29.290	-29.608
5	-28.780	-29.366<	-29.754
6	-28.643	-29.336	-29.794<
7	-28.461	-29.260	-29.789
8	-28.257	-29.163	-29.762

Notes: (1) Each VAR is estimated over the sample 2. week of 200 to 43. week of 2006

(2) < operator denotes the chosen lag.

7.2 APPENDIX ll : Emprical Results of Short-run Data

Table 7: VAR MODEL

I-Static Forecasting

	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.006	0.00107	0.00063	301.15	0.00159	307.97	0.00146	233.43
Dltr^	0.021	0.00735	0.00419	244.72	0.00363	133.52	0.00403	123.37
Dle^	0.0215	-0.00522	0.01266	100.56	0.01097	112.37	0.01475	101.59

Table 8:		**I(1) Cointegration Analysis**	
HO	H1	Cointegration eqution with constant term	Cointegration equation no constant term
r=0	r≥1	120.37 (0.000*)	103.41 (0.000*)
r≤ 1	r≥2	53.202 (0.000*)	42.741 (0.000*)
r≤ 2	r≥3	9.0917 (0.364)	9.2746 (0.154)
r≤ 3	r≥4	0.33206 (0.564)	1.1092 (0.341)

Notes: (1) Trace test statistics are given.

(2) Probability values are written in parenthesis.

Table 9: VECM with a constant term in the error correction equation

I-Static Forecasting results of VECM with a constant term in the error correction term

	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMS =	MAPE=	RMSE=	MAPE=
Dleuro^	0.00595	-0.0006	0.00136	1247.2	0.00251	956.04	0.00256	693.13
Dltr^	0.02099	0.00818	0.00521	293.31	0.00438	280.02	0.00534	259.91
Dle^	0.02125	-0.00579	0.01264	165.77	0.01144	137.54	0.01747	150.84

II- Dynamic Forecasting results of VECM with a constant term in the error correction equation								
	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00057	764.435	0.0015	1398.95	0.00219	885.959	0.00223	632.24
Dltr^	0.00814	119.171	0.00467	315.907	0.00397	273.355	0.00491	236.066
Dle^	0.00348	44.7461	0.01504	83.039	0.01228	113.018	0.01486	94.034

Table 10: VECM without a constant in the error correction equation

I- Static forecasting results of VECM								
	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00595	-0.00057	0.00128	1181.3	0.0024	901.7	0.00245	650.6
Dltr^	0.02096	0.00832	0.00519	267.86	0.00433	258.06	0.00526	239.8
Dle^	0.02118	-0.00546	0.01261	154.26	0.01115	132.1	0.01686	138.72

II- Dynamic forecasting results of VEC Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00105	1411.4512	0.00129	1206.28	0.0019	317.775	0.00152	122.42
Dltr^	0.00683	00.00027	0.00464	302.558	0.0039	222.968	0.00444	133.79
Dle^	0.00777	99.99897	0.01441	145.85	0.0114	118.26	0.01677	105.57

Table 11: MSVAR results with regime changes in intercept term

I- Static forecasting results of MSVAR Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00119	1597.4517	0.00095	509.9792	0.00164	333.951	0.00168	251.93
Dltr^	0.00695	101.7944	0.00413	242.7174	0.00353	181.207	0.00392	154.048
Dle^	0.00733	94.3032	0.01392	171.4554	0.01157	129.213	0.01445	115.137

II- Dynamic forecasting results of MSVAR Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00119	1597.452	0.00079	108.904	0.00146	138.481	0.00144	113.547
Dltr^	0.00695	101.794	0.00444	275.669	0.00363	180.359	0.00425	142.742
Dle^	0.00733	94.303	0.01434	154.782	0.01152	113.501	0.01643	108.141

Table 12
MSVECM with a constant term in the error correction equation
(with regime changes in intercept term)
I- Static forecasting results of MSVECM

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00053	707.8721	0.00108	867.2246	0.00167	528.9735	0.00171	380.9469
Dltr^	0.00476	69.7705	0.00328	665.1841	0.00374	466.6977	0.00401	369.8850
Dle^	0.00362	46.5875	0.01447	130.8163	0.01192	121.6713	0.01387	106.1627

II- Dynamic forecasting results of MSVEC Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00053	707.87	0.19532	115761.7	0.22783	116651.7	0.23850	84009.7
Dltr^	0.00476	69.771	0.03107	2623.45	0.05220	7645.395	0.05781	6679.29
Dle^	0.00362	46.588	0.20559	2758.803	0.31741	4096.427	0.34729	4954.18

Table 13
MSVECM without a constant term in the error correction equation
(with regime changes in intercept term)

I- Static forecasting results of MSVAR Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00053	707.92	0.00108	867.25	0.00167	528.99	0.00171	380.96
Dltr^	0.00476	69.78	0.00328	665.12	0.00374	466.66	0.00401	369.85
Dle^	0.00362	46.59	0.01447	130.82	0.01192	121.67	0.01387	106.16

II-Dynamic forecasting results of MSVEC Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00053	707.919	0.19533	115764.09	0.22784	116655.7	0.23851	84012.8
Dltr^	0.00476	69.775	0.03107	2623.361	0.05220	7645.54	0.05781	6679.46
Dle^	0.00362	46.589	0.20559	2758.8	0.31741	4096.53	0.34730	4954.33

Table 14								
MSVAR results with regime changes in intercept term and variance								
Static forecasting results of MSVAR Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00031	418.4436	0.00127	349.8833	0.00151	216.4772	0.0015	167.367
Dltr^	0.00703	103.0032	0.00379	95.20542	0.00376	96.36354	0.00442	100.602
Dle^	0.00750	96.4649	0.01605	173.9391	0.01293	135.5857	0.01502	115.848
II- Dynamic forecasting results of MSVAR Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00031	418.444	0.00108	223.353	0.00132	178.286	0.00138	141.295
Dltr^	0.00703	103.003	0.00404	132.479	0.00388	144.556	0.00412	121.103
Dle^	0.00750	96.465	0.01454	121.532	0.01166	100.759	0.01610	102.473

Table 15

MSVECM with a constant term in the error correction equation

with regime changes in intercept term and variance

I- Static forecasting results of MSVECM Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00084	1123.58	0.00096	782.161	37.41291	467.661	0.00158	339.586
Dltr^	0.00709	103.789	0.00369	181.17	13.10339	163.792	0.00414	149.871
Dle^	0.00805	103.59	0.01669	185.858	11.46243	143.280	0.01495	119.609

II- Dynamic forecasting results of MSVECM Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00084	1123.58	0.00076	700.982	0.00147	494.768	0.00169	359.128
Dltr^	0.00709	103.789	0.00331	138.036	0.0033	121.964	0.00362	118.865
Dle^	0.00805	103.585	0.01432	135.79	0.01136	116.278	0.01644	109.593

Table 16
MSVECM without a constant term in the error correction equation
with regime changes in intercept term and variance

I- Static forecasting results of MSVECM Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00084	1123.619	0.00096	782.187	0.00144	467.675	0.00158	339.6
Dltr^	0.00709	103.7898	0.00369	181.1598	0.00361	163.787	0.00414	149.87
Dle^	0.00805	103.5857	0.01669	185.858	0.01322	143.281	0.01495	119.61

II- Dynamic forecasting results of MSVECM Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00084	1123.619	0.00076	701.011	0.00147	494.785	0.00169	359.14
Dltr^	0.00709	103.7898	0.00331	138.032	0.00330	121.962	0.00362	118.86
Dle^	0.00805	103.5857	0.01432	135.791	0.01136	116.278	0.01644	109.59

Table 17

MSVAR results

with regime changes in intercept term, variance and coefficients

I- Static forecasting results of MSVAR Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00085	1136.3	0.00129	524.225	0.00157	308.274	0.00156	227.01
Dltr^	0.00725	106.248	0.00421	264.844	0.00362	191.148	0.00372	152.612
Dle^	0.00871	112.096	0.01506	117.619	0.01221	97.9295	0.01517	97.0864

II- Dynamic forecasting results of MSVAR Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00085	1136.3	0.00114	262.657	0.00132	212.365	0.00148	162.786
Dltr^	0.00725	106.248	0.00430	143.81	0.00373	190.3195	0.00431	148.883
Dle^	0.00871	112.096	0.01472	101.917	0.01141	107.312	0.01545	113.033

Table 18

MSVECM with a constant term in the error correction equation

with regime changes in intercept term, variance and coefficients

I- Static forecasting results of MSVECM Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00072	959.589	0.00099	764.712	0.00146	459.445	0.00157	332.613
Dltr^	0.00494	72.315	0.00304	519.483	0.00329	375.063	0.00354	311.862
Dle^	0.00845	108.77	0.01570	121.655	0.01241	101.232	0.01482	97.239

II- Dynamic forecasting results of MSVECM Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00072	959.589	0.00073	626.01	0.00138	401.803	0.00160	288.824
Dltr^	0.00494	72.315	0.00293	731.28	0.00420	629.405	0.00433	505.948
Dle^	0.00845	108.77	0.01458	90.025	0.01201	85.9997	0.01553	95.3851

Table 19								
MSVECM without a constant term in the error correction equation								
with regime changes in intercept term, variance and coefficients								
I- Static forecasting results of MSVECM Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00072	959.2102	0.00099	764.4829	0.00146	459.321	0.00157	332.526
Dltr^	0.00494	72.31509	0.00304	519.4789	0.00329	375.06	0.00354	311.860
Dle^	0.00845	108.7679	0.01570	121.6538	0.01241	101.232	0.01482	97.2390
II- Dynamic forecasting results of MSVECM Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00072	959.210	0.00073	625.752	0.00138	401.649	0.00160	288.717
Dltr^	0.00494	72.315	0.00293	731.277	0.00420	629.408	0.00433	505.95
Dle^	0.00845	108.768	0.01458	90.02	0.01201	85.996	0.01553	0.0155

Table 20		
Model Comparision of short run data		
I- Static forecasting results		
	Dleuro^	
1-STEP	RMSE	MSVAR(VARIANCE)
	MAPE	MSVAR(VARIANCE)
4-STEP	RMSE	VAR
	MAPE	VAR
8-STEP	RMSE	MSVECMNOCONSTANT(variance)
	MAPE	MSVAR(VARIANCE)
12-STEP	RMSE	VAR
	MAPE	MSVAR(VARIANCE)

I- Static forecasting results		
Dltr^		
1-STEP	RMSE	MSVECMNOCONSTANT(NONE)
	MAPE	MSVECMNOCONSTANT(NONE)
4-STEP	RMSE	MSVECMNOCONSTANT(variance&coefficients)
	MAPE	MSVAR(VARIANCE)
8-STEP	RMSE	MSVECMNOCONSTANT(variance&coefficients)
	MAPE	MSVAR(VARIANCE)
12-STEP	RMSE	MSVECMNOCONSTANT(variance&coefficients)
	MAPE	MSVAR(VARIANCE)

I- Static forecasting results		
Dle^		
1-STEP	RMSE	MSVECM-withCONSTANT(NONE)
	MAPE	MSVECM-withCONSTANT(NONE)
4-STEP	RMSE	VECMNOCONSTANT
	MAPE	VAR
8-STEP	RMSE	VAR
	MAPE	MSVAR(VARIANCE&COEFICIENTS)
12-STEP	RMSE	MSVECM-withCONSTANT(NONE)
	MAPE	MSVAR(VARIANCE&COEFICIENTS)

II- Dynamic Forecasting Results		
Dleuro^		
1-STEP	RMSE	MSVAR(VARİANCE)
	MAPE	MSVAR(VARİANCE)
4-STEP	RMSE	MSVECMnoconstant(VARIANCE&COEFFICIENTS)
	MAPE	MSVAR(NONE)
8-STEP	RMSE	MSVECM-CONSTANT(VARİANCE&COEFFICIENTS)
	MAPE	MSVAR(NONE)
12-STEP	RMSE	MSVAR(VARİANCE)
	MAPE	MSVAR(NONE)

II- Dynamic Forecasting Results		
Dltr^		
1-STEP	RMSE	MSVECM-CONSTANT(NONE)
	MAPE	MSVECM-CONSTANT(NONE)
4-STEP	RMSE	MSVECMnoconstant(VARIANCE&COEFFICIENTS)
	MAPE	MSVAR(VARİANCE)
8-STEP	RMSE	MSVECM-CONSTANT(VARİANCE)
	MAPE	MSVECMnoconstant(VARIANCE)
12-STEP	RMSE	MSVECM-CONSTANT(VARİANCE)
	MAPE	MSVECMnoconstant(VARIANCE)

II- Dynamic Forecasting Results		
Dle^		
1-STEP	RMSE	VECM WITH CONSTANT
	MAPE	VECM WITH CONSTANT
4-STEP	RMSE	MSVAR(NONE)
	MAPE	VECM WITH CONSTANT
8-STEP	RMSE	MSVECMnoconstant(VARIANCE)
	MAPE	MSVECMnoconstant(VARIANCE&COEFFICIENTS)
12-STEP	RMSE	VECM WITH CONSTANT
	MAPE	VECM WITH CONSTANT

Notes:

- 'NONE' , 'VARIANCE' and ' VARIANCE& COEFFICIENTS', written in the brackets, represent the regime changes in the intercept, the intercept and variance, and in the intercept, variance and coefficients.

-VECMnoCONSTANT denotes VECM without a constant term in the error correction term.

-VECMwithCONSTANT represents VECM with a constant term in the error correction term.

-MS is the abbriviation of Markov Switching .

Table 21:LR test statistics				
	(LR) LİNEARITY TEST	chi(p)	chi(p+q)	Davies upper bound
MSVAR (NONE)	287.278	Chi(3)=[0.00]	Chi(5)=[0.00]**	[0.00]**
MSVAR (VARIANCE)	990.366	Chi(9)=[0.00]**	Chi(11)=[0.00]**	[0.00]**
MSVAR (VAR&COEFF)	948.682	Chi(33)=[0.00]*	Chi(35)=[0.00]**	[0.00]**
MSVECMnoCONSTANT (NONE)	234.926	Chi(3)=[0.00]**	Chi(5)=[0.00]**	[0.00]**
MSVECMnoCONSTANT (VARIANCE)	1026.026	Chi(9)=[0.00]**	Chi(11)=[0.00]**	[0.00]**
MSVECMnoCONSTANT (VAR&COEFF)	1033.505	Chi(27)=[0.00]**	Chi(29)=[0.00]**	[0.00]**
MSVECMwithCONSTANT (NONE)	234.926	Chi(3) =[0.00]**	Chi(5)=[0.00]**	[0.00]**
MSVECMwithCONSTANT (VARIANCE)	1026.02	Chi(9)=[0.00]**	Chi(11)=[0.00]**	[0.00]
MSVECMwithCONSTANT (VAR&COEFF)	1033.50	Chi(27)=[0.00]**	Chi(29)=[0.00]**	[0.00]**

Notes:

-In the column two, three and four, test statistics are represented with probability values.

- 'NONE' , 'VARIANCE' and ' VAR& COEFF', written in the brackets, represent the regime changes in the intercept, the intercept and variance, and in the intercept, variance and coefficients.

-VECMnoCONSTANT denotes VECM without a constant term in the error correction term.

-VECMwithCONSTANT represents VECM with a constant term in the error correction term.

-MS is the abbriviation of Markov Switching .

Table 22-Information Criteria test results						
				Linear Model		
	AIC	HQ	SC	AIC	HQ	SC
MSVAR (NONE)	-17.8463	-17.68	-17.4284	-17.0564	-16.9119	-16.6934
MSVAR(VARIANE)	-19.8152	-19.622	-19.3313	-17.0564	-16.9119	-16.6934
MSVAR (VARIANCE &COEFFICIENTS)	-19.5597	-19.262	-18.8118	-17.0564	-16.9119	-16.6934
MSVECMwithCONSTANT (NONE)	-17.7525	-17.612	-17.4013	-17.1135	-16.9956	-16.8172
MSVECMwithCONSTANT (VARIANCE)	-19.9659	-19.799	-19.5488	-17.1135	-16.9956	-16.8172
MSVECMwithCONSTANT (VARIANCE &COEFFICIENTS)	-19.8848	-19.640	-19.2702	-17.1135	-16.9956	-16.8172
MSVECMnoCONSTANT (NONE)	-17.7525	-17.6127	-17.4013	-17.1135	-16.9956	-16.8172
MSVECMnoCONSTANT (VARIANCE)	-19.9659	-19.7999	-19.5488	-17.1135	-16.9956	-16.8172
MSVECMnoCONSTANT (VARIANCE &COEFFICIENTS)	-19.8848	-19.6402	-19.2702	-17.1135	-16.9956	-16.8172

Notes:

- 'NONE' , 'VARIANCE' and ' VARIANCE& COEFFICIENTS', written in the brackets, represent the regime changes in the intercept, the intercept and variance, and in the intercept, variance and coefficients.

-VECMnoCONSTANT denotes VECM without a constant term in the error correction term.

-VECMwithCONSTANT represents VECM with a constant term in the error correction term.

-MS is the abbriviation of Markov Switching .

7.3 APPENDIX llI: Emprical Results of Long-run Data

Table 23:VAR MODEL

I- Static Forecasting Results of VAR(2) Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.004743	0.000635	0.00087	239.15	0.001002	306	0.00092	871.37
Dltr^	0.01851	0.00356	0.00199	122.8	0.002775	100.33	0.00263	128.01
Dle^	0.02116	-0.00769	0.01135	147.31	0.011678	101.28	0.01126	93.996

II- Dynamic Forecasting Results of VAR(2) Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00063	345.83	0.00277	932.63	0.0494	26651.23	0.064	33801.64
Dltr^	0.00355	127.25	0.26896	42664.6	0.3755	42592.75	0.4291	38258.8
Dle^	0.00767	61.095	0.01249	161.77	0.0962	693.076	0.1494	1513.273

Table 24 :(I(1) Cointegration Analysis)

HO	H1	Cointegration eqution with constant term	Cointegration equation no constant term
r=0	r≥1	138.55 (0.000*)	120.66 (0.000*)
r≤ 1	r≥2	53.868 (0.000*)	42.389 (0.000*)
r≤ 2	r≥3	8.3446 (0.437)	7.2450 (0.303)
r≤ 3	r≥4	0.49180 (0.483)	1.1885 (0.322)

Notes:

- Trace test statistics are given.

- Probability values are written in parenthesis.

Table 25: VECM with a constant term in the error correction equation

I- Static forecasting results of VECM

	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00504	-0.00115	0.0027	2185.3	0.0028	1746.9	0.0029	4118.8
Dltr^	0.01839	0.00244	0.00168	102.25	0.0029	119.83	0.00251	114.27
Dle^	0.02093	-0.00927	0.01544	194.33	0.0138	161.34	0.01345	144.5

II- Dynamic Forecasting results of VECM

	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00087	472.6995	0.00254	2285.60	0.00152	726.05	0.00148	2529.57
Dltr^	0.00271	97.25268	0.00228	115.074	0.00280	89.756	0.00249	113.118
Dle^	0.00931	74.15330	0.01755	13.6996	0.01384	142.28	0.01290	112.837

Table 26: VECM without a constant in the error correction term

I- Static forecasting results of VECM

	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.005	-0.0011	0.0026	2083.3	0.00264	1643.7	0.00274	3771.1
Dltr^	0.01839	0.00258	0.00168	85.688	0.00281	105.33	0.00249	108.55
Dle^	0.02091	-0.00904	0.01497	188.34	0.0135	155.36	0.0131	137.24

II- Dynamic Forecasting results of VECM

	1-STEP		4-STEP		8-STEP		12-STEP	
	SE=	ERROR=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00079	430.7646	0.00241	2188.67	0.00140	648.341	0.00139	2306.18
Dltr^	0.00285	102.2292	0.00225	101.15	0.00277	89.7058	0.00251	112.023
Dle^	0.00906	72.13007	0.01692	207.213	0.01350	134.463	0.01268	104.587

Table 27: MSVAR results with regime changes in intercept term

I- Static forecasting results of MSVAR

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00077	418.453	0.00091	325.588	0.00115	259.586	0.00111	823.607
Dltr^	0.00484	173.522	0.00255	197.37	0.00247	138.785	0.00306	188.856
Dle^	0.01188	94.592	0.01135	136.38	0.01255	118.77	0.01246	107.290

II- Dynamic Forecasting results of MSVAR

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00077	418.4534	0.00062	211.142	0.00091	190.799	0.00088	1154.53
Dltr^	0.00484	173.5224	0.00184	99.729	0.00276	84.1083	0.00288	137.648
Dle^	0.01188	94.5918	.01358	156.273	0.01328	120.919	0.01311	108.293

Table 28

MSVECM with a constant term in the error correction equation

with regime changes in intercept term

Static forecasting results of MSVEC Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00113	617.004	0.00148	887.772	0.00146	670.732	0.00146	1798.24
Dltr^	0.00007	2.4543	0.00255	280.112	0.00390	252.739	0.00323	190.792
Dle^	0.00725	57.758	0.00876	122.816	0.01253	120.13	0.01180	109.036

with regime switching in intercept term

II- Dynamic forecasting results of MSVECM Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00113	617.004	0.00168	965.841	0.00167	713.276	0.00178	2103.25
Dltr^	0.00007	2.4543	0.00289	370.18	0.00374	273.825	0.00291	199.048
Dle^	0.00725	57.7584	0.01370	172.438	0.01327	121.221	0.01235	106.696

Table 29

MSVECM without a constant term in the error correction equation

with regime changes in intercept term

I- Static forecasting results of MSVEC Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00113	616.92	0.00148	887.64	0.00146	670.64	0.00146	1797.96
Dltr^	0.10513	3766.16	0.10178	13913.15	0.10130	10418.06	0.10162	9431.51
Dle^	0.00725	57.76	0.00876	122.825	0.01253	120.136	0.01180	109.039

II- Dynamic forecasting results of MSVEC Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00113	616.922	0.00168	965.70	0.00167	713.165	0.00178	2102.9
Dltr^	0.00007	2.4503	0.00289	370.21	0.00374	273.848	0.00291	199.065
Dle^	0.00725	57.7633	0.01370	172.446	0.01327	121.225	0.01236	106.698

Table 30: MSVAR results with regime changes in intercept and variance

I- Static forecasting results of MSVAR Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00069	377.7089	0.00074	280.601	0.00104	198.446	0.00095	614.311
Dltr^	0.00464	166.0676	0.00259	231.453	0.00274	170.181	0.00259	162.363
Dle^	0.00816	65.0162	0.01066	148.311	0.01394	130.446	0.01282	118.138

II- Dynamic forecasting results of MSVAR Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00069	377.7089	0.00052	212.856	0.00085	176.03	0.00080	616.618
Dltr^	0.00464	166.0676	0.00233	206.142	0.00288	149.509	0.00285	155.284
Dle^	0.00817	65.0279	0.01243	165.327	0.01302	98.621	0.01231	96.6037

Table 31								
MSVECM with a constant term in the error correction equation								
with regime changes in intercept teerm and variance								
I- Static forecasting results of MSVECM Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00022	120.3928	0.00094	619.169	0.00097	407.391	0.00099	821.02
Dltr^	0.00242	86.5539	0.00227	126.972	0.00299	123.236	0.00251	99.825
Dle^	0.00868	69.1388	0.0115	160.825	0.01413	140.217	0.01292	123.447
II- Dynamic forecasting results of MSVECM Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00022	120.3928	0.00105	703.733	0.00105	374.62	0.00115	1001.95
Dltr^	0.00242	86.5539	0.00280	176.118	0.00280	126.43	0.00237	109.737
Dle^	0.00868	69.1388	0.01331	189.395	0.01331	118.77	0.01241	106.202

Table 32								
MSVECM without a constant term in the error correction equation								
with regime changes in intercept term and variance								
I- Static forecasting results of MSVECM Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00022	120.742	0.00094	619.716	0.00097	407.779	0.00099	822.179
Dltr^	0.00242	86.5749	0.00228	127.041	0.00299	123.277	0.00251	99.866
Dle^	0.00868	69.142	0.01150	160.831	0.01413	140.221	0.01292	123.448
II- Dynamic forecasting results of MSVEC Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00022	120.7424	0.00111	704.323	0.00105	375.11	0.00115	1003.37
Dltr^	0.00242	86.5749	0.00231	176.006	0.00280	126.34	0.00237	109.727
Dle^	0.00868	69.1422	0.01463	189.409	0.01331	118.78	0.01241	106.209

Table 33								
MSVAR								
with regime changes in intercept term, variance and coefficients								
I- Static forecasting results of MSVAR Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00059	320.503	0.0007	211.485	0.00103	185.125	0.00095	701.77
Dltr^	0.00364	130.432	0.00271	295.895	0.00291	231.02	0.00264	196.83
Dle^	0.00689	54.8934	0.01102	161.709	0.01408	140.05	0.01284	123.49
II- Dynamic forecasting results of MSVAR Model								
	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	0.00059	320.503	0.00047	156.776	0.00082	185.015	0.00080	735.399
Dltr^	0.00364	130.432	0.00273	219.996	0.00275	143.214	0.00278	147.75
Dle^	0.00689	54.8934	0.01288	180.688	0.01285	97.5865	0.01213	95.619

Table 34
MSVECM with a constant term in the error correction equation
with regime switching in intercept, variance and coefficients

I- Static forecasting results of MSVEC Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	5.385E-07	0.2938	0.00067	333.132	0.00086	242.662	0.00085	300.483
Dltr^	0.00159	56.8422	0.00224	95.6804	0.00342	109.09	0.00281	83.8757
Dle^	0.00689	54.8539	0.01085	154.387	0.01447	133.537	0.01306	122.649

II- Dynamic forecasting results of MSVEC Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	5.385E-07	0.2938	0.00071	369.48	0.00087	212.814	0.00086	259.95
Dltr^	0.00159	56.8422	0.00233	40.5617	0.00317	182.71	0.00251	129.87
Dle^	0.00689	54.8539	0.01316	176.192	0.01300	97.24	0.01202	97.028

Table 35
MSVECM without a constant term in the error correction equation
with regime changes in intercept term, variance and coefficients

I- Static forecasting results of MSVECM Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	6.377E-07	0.3479	0.00067	333.216	0.00086	242.722	0.00085	300.66
Dltr^	0.00159	56.8542	0.00224	95.6461	0.00342	109.077	0.00281	83.864
Dle^	0.00689	54.8579	0.01085	154.394	0.01447	133.54	0.01306	122.65

II- Dynamic forecasting results of MSVEC Model

	1-STEP		4-STEP		8-STEP		12-STEP	
	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=	RMSE=	MAPE=
Dleuro^	6.377E-07	0.34790	0.00071	369.564	0.00087	212.816	0.00086	260.09
Dltr^	0.00159	56.8542	0.00233	240.505	0.00316	182.666	0.00251	129.84
Dle^	0.00689	54.8579	0.01316	176.201	0.01300	97.2477	0.01202	97.032

Table- 36 Model comparison of Long run data		
I- Static Forecasting results		
Dleuro^		
1-STEP	RMSE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
	MAPE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
4-STEP	RMSE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
	MAPE	MSVAR(VARIANCE&COEFFICIENTS)
8-STEP	RMSE	MSVECMnoCONSTANT(VARIANCE&COEFFICIENTS)
	MAPE	MSVAR(VARIANCE&COEFFICIENTS)
12-STEP	RMSE	MSVECMnoCONSTANT(VARIANCE&COEFFICIENTS)
	MAPE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)

I- Static Forecasting results		
Dltr^		
1-STEP	RMSE	MSVECMwithCONSTANT(NONE)
	MAPE	MSVECMwithCONSTANT(NONE)
4-STEP	RMSE	VECM NO CONSTANT
	MAPE	VECM NO CONSTANT
8-STEP	RMSE	MSVAR(NONE)
	MAPE	VAR
12-STEP	RMSE	VECM NO CONSTANT
	MAPE	MSVECMnoCONSTANT(VARIANCE&COEFFICIENTS)

I- Static Forecasting results		
Dle^		
1-STEP	RMSE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
	MAPE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
4-STEP	RMSE	MSVECMnoCONSTANT(NONE)
	MAPE	MSVECMwithCONSTANT(NONE)
8-STEP	RMSE	VAR
	MAPE	VAR
12-STEP	RMSE	VAR
	MAPE	VAR
II- Dynamic Forcasting Results		
Dleuro^		
1-STEP	RMSE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
	MAPE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
4-STEP	RMSE	MSVAR(VARIANCE&COEFFICIENTS)
	MAPE	MSVAR(VARIANCE&COEFFICIENTS)
8-STEP	RMSE	MSVAR(VARIANCE&COEFFICIENTS)
	MAPE	MSVAR(VARIANCE)
12-STEP	RMSE	MSVAR(VARIANCE)
	MAPE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)

II- Dynamic Forecasting Results		
Dltr^		
1-STEP	RMSE	MSVECMnoCONSTANT(NONE)
	MAPE	MSVECMnoCONSTANT(NONE)
4-STEP	RMSE	MSVAR(NONE)
	MAPE	MSVAR(NONE)
8-STEP	RMSE	MSVAR(VARIANCE&COEFFICIENTS)
	MAPE	MSVAR(NONE)
12-STEP	RMSE	MSVECMnoCONSTANT(VARIANCE)
	MAPE	MSVECMnoCONSTANT(VARIANCE)

II-Dynamic Forecasting results		
Dle^		
1-STEP	RMSE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
	MAPE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
4-STEP	RMSE	MSVAR(VARIANCE)
	MAPE	MSVAR(VARIANCE)
8-STEP	RMSE	MSVAR(VARIANCE&COEFFICIENTS)
	MAPE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
12-STEP	RMSE	MSVECMwithCONSTANT(VARIANCE&COEFFICIENTS)
	MAPE	MSVAR(VARIANCE&COEFFICIENTS)

Notes:

- 'NONE' , 'VARIANCE' and 'VARIANCE& COEFFICIENTS', written in the brackets, represent the regime changes in the intercept, the intercept and variance, and in the intercept, variance and coefficients.

-VECMnoCONSTANT denotes VECM without a constant term in the error correction term.

-VECMwithCONSTANT represents VECM with a constant term in the error correction term.

-MS is the abbriviation of Markov Switching .

Table 37:LR test statistics				
	LR TEST	chi(p)	chi(p+q)	Davies upper bound
MSVAR (NONE)	120.482	Chi(3)=[0.00]	Chi(5)=[0.00]**	[0.00]**
MSVAR (VARIANCE)	864.2314	Chi(9)=[0.00]**	Chi(11)=[0.00]**	[0.00]**
MSVAR (VAR&COEFF)	918.5133	Chi(33)=[0.00]**	Chi(35)=[0.00]**	[0.00]**
MSVECMnoCONSTANT (NONE)	189.6028	Chi(3)=[0.00]**	Chi(5)=[0.00]**	[0.00]**
MSVECMnoCONSTANT (VARIANCE)	916.1671	Chi(9)=[0.00]**	Chi(11)=[0.00]**	[0.00]**
MSVECMnoCONSTANT (VAR&COEFF)	972.135	Chi(27)=[0.00]**	Chi(29)=[0.00]**	[0.00]**
MSVECMwithCONSTANT (NONE)	189.6028	Chi(3)=[0.00]**	Chi(5)=[0.00]**	[0.00]**
MSVECMwithCONSTANT (VARIANCE)	916.1671	Chi(9)=[0.00]**	Chi(11)=[0.00]**	[0.00]
MSVECMwithCONSTANT (VAR&COEFF)	972.135	Chi(27)=[0.00]**	Chi(29)=[0.00]**	[0.00]**

NoteS:

-In the column two, three and four, test statistics are represented with probability values.

- 'NONE' , 'VARIANCE' and 'VAR& COEFF', written in the brackets, represent the regime changes in the intercept, the intercept and variance, and in the intercept, variance and coefficients.

-VECMnoCONSTANT denotes VECM without a constant term in the error correction term.

-VECMwithCONSTANT represents VECM with a constant term in the error correction term.

-MS is the abbriviation of Markov Switching .

Table 38: Information Criteria test results

				Linear Model		
	AIC	HQ	SC	AIC	HQ	SC
MSVAR (NONE)	-18.1255	-17.9599	-17.709	-17.8125	-17.6687	-17.451
MSVAR (VARIANE)	-20.1985	-20.0067	-19.717	-17.8125	-17.6687	-17.451
MSVAR (VARIANCE &COEFFICIENTS)	-20.2162	-19.9199	-19.471	-17.8125	-17.6687	-17.451
MSVECMwithCONSTANT (NONE)	-18.2833	-18.1441	-17.934	-17.776	-17.6585	-17.481
MSVECMwithCONSTANT (VARIANCE)	-20.3018	-20.1366	-19.887	-17.776	-17.6585	-17.481
MSVECMwithCONSTANT (VARIANCE &COEFFICIENTS)	-20.3583	-20.1147	-19.746	-17.776	-17.6585	-17.4808
MSVECMnoCONSTANT (NONE)	-18.2833	-18.1441	-17.934	-17.776	-17.6585	-17.4808
MSVECMnoCONSTANT (VARIANCE)	-20.3018	-20.1366	-19.887	-17.776	-17.6585	-17.481
MSVECMnoCONSTANT (VARIANCE &COEFFICIENTS)	-20.3583	-20.1147	-19.746	-17.776	-17.6585	-17.481

Notes:

- 'NONE' , 'VARIANCE' and 'VARIANCE& COEFFICIENTS', written in the brackets, represent the regime changes in the intercept, the intercept and variance, and in the intercept, variance and coefficients.

-VECMnoCONSTANT denotes VECM without a constant term in the error correction term.

-VECMwithCONSTANT represents VECM with a constant term in the error correction term.

-MS is the abbriviation of Markov Switching .