The role of Regime Shifts in the Term Structure of Interest Rates: Further evidence from an Emerging Market

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Abstract

In this paper, we investigate the interrelations among Turkish interest rates with different maturities by using a regime switching Vector Error Correction (VECM) model. We find a long run equilibrium relationship among interest rates with various maturities. Furthermore we conclude that term structure dynamics exhibit significant nonlinearity. Forecasting experiment also reveals that the nonlinear term structure models do fare better than other linear specifications. However, we cannot conclude that interest rate adjustments are made in an asymmetric way in the long run equilibrium.

JELClassification: C32, C52, C53, E43

Key Words: Term Structure of Interest Rates, Regime Switching, Forecasting, Forecast Evaluation, Cointegration

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1. Introduction

Studies on term structure dynamics have always been at the core of macroeconomics and finance research. Campbell and Clarida (1986), Campbell and Shiller (1987) and Hall et al (1992) studied the long-run dynamics of term structure of interest rates. Recently, Diebold and Li (2007) has extended the popular static yield curve model developed by Nelson and Siegel (1987). With an innovative structure Diebold and Li (2007) enabled researchers to forecast the interest rates via linear models. Two improved versions of Diebold and Li (2007) are Diebold et al (2011) and Diebold et al (2008). Recently, Clarida et. al. (2006) proposed a nonlinear multivariate vector error correction (VECM) model to investigate the term structure of interest rates by incorporating the potential asymmetries in the error correction mechanism. They also studied the weekly forecasting performance of the nonlinear dynamic interest rate model against some linear benchmark models. Despite the importance of these developments, relatively few studies addressed the dynamics of term structure of interest rates in emerging markets[1]. However, none of these studies, except Guillen and Tabak (2008) for the Brazilian case, explicitly addressed the nonlinearity of term structure of interest rates. During the last two decades, Turkish economy has experienced a number of sharp downturns and economic crises[2]. These have a direct impact on the interest rates and term structure of interest rates. As a result, term structure dynamics of the Turkish economy can be better investigated under nonlinear

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[1] For instance, Alper et al. (2007) provided an analysis of term structure of interest rates for Turkey. Telatar et al. (2003) examined the information content in term structure of interest rate about future inflation by using time-varying-parameter model. Kaya and Yazgan (2009) emphasized the effect of monetary policy change on the nature of this information content.

[2] See Yilmazkuday and Akay (2008) for a brief account of these developments and an analysis of business cycles of Turkish economy in regime switching approach.

models. First of all Turkish economy has experienced a long inflationary period during the last three decades. Until the last 8-9 years Turkish inflation rates were around double or even triple digit levels. However, time to time Turkish policy makers want to halt hyper inflation via various tools. So the economy had high and low inflationary periods with very high and relatively milder interest rates. Therefore, nonlinearity is a necessary aspect of modeling in the Turkish interest rate markets. Morever, it is also interesting to see whether the short run adjustments towards equilibrium is symmetric or not. It is important to compare the speed of adjustment towards equilibrium when the economy is in relatively high inflationary environment with that of when the economy is in the low inflationary environment. In other words, if the inflationary expectations hit a positive shock how fast can this shock be dissipated compared to a negative inflationary shock. This asymmetry has important policy implications for central banks and monetary policy which needs to be investigated.

In this paper, we wish to fill these gaps in empirical macroeconomics. Following Clarida et al (2006) we analyze the term structure dynamics of the Turkish interest rates by using the weekly Turkish interest rate data between 1993 and 2009. We empirically test the existence of nonlinearity in the term structure of interest rates. We conduct a weekly forecasting experiment on the Turkish interest rates with different maturities. In addition to these, we extend the regime switching specification by allowing the speed of adjustment coefficients to change across regimes. Furthermore, we adopt the reality check methodology of White (2000) to test the adequacy of forecasts generated by the various alternative nonlinear and asymmetric models.

Consequently, we obtain three main results: First we conclude that long run relationships among various interest rates exist, which supports the predictions of expectation hypothesis. We also demonstrate that there exists a nonlinear regime switching structure in the weekly interest rate data we study. Finally, we have shown that negative and positive interest rates shocks do behave differently. This finding on asymmetry is particularly important for the central bank and monetary policy since it is directly related to the credibility of central bank. Furthermore, negative spreads between long and short maturity of interest rates usually are very rare in the Turkish data (see Figure 1 below). But negative spreads usually predate crisis and recessions periods. Therefore negative spreads and shocks tend to be short lasting than that of positive spreads. So our findings on asymmetry is in line with empirical facts in Turkish economy. However, forecasts generated by symmetric nonlinear regime switching models beat the other alternative linear vector time series models. This result suggests that an asymmetric adjustment in the interest rate modeling do exist but not strong enough to generate a better prediction performance in our interest rate data. This may be related to the fact that in the recent data where we have conducted our forecasting exercise there is not enough asymmetric data. Therefore, even though we can capture the asymmetry in the data it cannot be useful for forecasting. To the best of our knowledge, this is the first comprehensive attempt on analyzing the term structure dynamics on an emerging market economy. From the Turkish economy point of view our research will have some important implications. First of all, as the inflation drops, the shape of the yield curve becomes more informative. In addition, the asymmetry between the negative and positive term spread may also have different implications for monetary policy.

The organization of the paper is as follows: In the following section, we discuss the theories of term structure and in section three we discuss its estimation through nonlinear dynamic time series models. In the fourth section we present our empirical results. We conclude in the final section.

2. Cointegration and the expectations hypothesis

Expectations hypothesis (EH) can be formulated as follows (see Clarida et al., 2006 and Campbell and Shiller, 1991)

$$R_{k,t} = \frac{1}{k}\sum_{j=1}^{k-1} E_t(R_{1,t+j-1}) + \gamma_{k,t} \qquad (1)$$

where $R_{k,t}$ is the yield to maturity obtained from a *k*-period pure discount bond. As is known, this equation can be interpreted as the longer term spot rates are equal to the average expected short rate of interests. If we subtract $R_{1,t}$ from both sides of equation (1) we obtain the following equation

$$R_{k,t} - R_{1,t} = \frac{1}{k}\left(\sum_{m=1}^{k-1}\sum_{j=1}^{m} \Delta E_t R_{1,t+j}\right) + \gamma_{k,t} \qquad (2)$$

where Δ is the first difference operator and E_t refers to the expectation operator conditioned on information available time *t*. The last term in this equation refers to the time varying term premia. More specifically, the term spread between long and short term of maturities should be explained by first difference of interest rates with various maturities. Therefore, equation above has testable implications. In this formulation, if we allow a time varying and stationary term premia, $\gamma_{k,t}$ and if we assume that the interest rates are integrated order one, I(1), the above equation implies a cointegrating relationship between the term spread (i.e. the difference between interest rate of maturity *k* and *l),* In other words, if the theoretical predictions of the above model is correct then term spread should follow I(0) i.e. $R_{k,t} - R_{1,t} \sim I(0)$. More concretely, the interest rates of maturity *k* and *1* are cointegrated with a vector $[1,-1]'$. Hence, according to EH, if we have *n* interest rates of different maturities, there must be exactly $n-1$ distinct co-integrating relationships among them. Each of these cointegrating vectors are given by stationary spreads between $R_{k,t} - R_{1,t}$ for $k = 2,...,n$. As is well known, given the existence of cointegrating relationships between a set of interest rates of different maturities, the dynamic relationships between them can formulated within a vector error correction model (VECM).

3. Modeling Term Structure Nonlinearities via Regime-Switching Vector Error Correction Model (RSVECM)

Term structure of interest rates is very much affected by economic growth and business cycles. Consequently, the levels and the term structure of interest rates have varying dynamics in different economic regimes. Recent studies on Regime Switching models by Hamilton (1983), Krolzig (1997) have investigated the properties of regime switching econometric models both in univariate and multivariate contexts.

Consider the following Markov Switching (MS) VECM process:

$$\Delta \mathbf{y}_t = \mathbf{v}(s_t) + \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{y}_{t-1} + \sum\nolimits_{i=1}^{p} \boldsymbol{\Gamma}_i \Delta \mathbf{y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{3}$$

where $\mathbf{y}_t$ is an n dimensional time series vector observed at time t and T is the sample size. In our specific example n is equal to 5 and the vector $\mathbf{y}$ contains interest rates at 90, 120,180, 270 and 360 days maturities i.e $y_t = (R_{90,t}, R_{120,t}, R_{180,t}, R_{270,t}, R_{360,t})'$. The $n \times r$ order $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ matrices contain the factor-loading (or speed of adjustment) and co-integration vectors where r is the number of co-integrating vectors. $\boldsymbol{v}$ is the vector of intercepts, $\boldsymbol{\Gamma}_1, \ldots, \boldsymbol{\Gamma}_p$ are the matrices containing the autoregressive parameters and $\boldsymbol{\varepsilon}_\mathbf{t}$ is a white noise vector process such that $\boldsymbol{\varepsilon}_\mathbf{t} \mid s_t \sim NID \ \left(\mathbf{0}, \boldsymbol{\Sigma}(s_t)\right)$. The regime generating process is assumed to be an ergodic Markov chain with a finite number of states $s_t \in [1,...,M]$ governed by transition probabilities $p_{ij} = \Pr\left(s_{t+1} = j / s_t = i\right)$ and $\sum\nolimits_{j=1}^{M} p_{ij} = 1$ for all $i, j \in \{1,...,M\}$. This type of MS VECM model, which allows regime shifts, both in intercept[3] and variance and covariance matrix, is termed as

[3] Note that the intercept $\mathbf{v}$ controls the mean of $\mathbf{y}_t$ through the relationship $\boldsymbol{\mu}(s_t) = \mathbf{v}(s_t)\left\{\mathbf{I} - \boldsymbol{\Pi}_1(s_t) - \cdots - \boldsymbol{\Pi}_p(s_t)\right\}^{-1}$. An alternative representation is obtained by allowing the mean to vary with the state.

Markov-switching-intercept- heteroskedastic- VECM (MSIH-VECM) after Krolzig (1996).

As indicated by Clarida et.al. (2006) the asymmetric adjustment in interest rates, can be modeled within this framework. To capture the asymmetries in the data they write the above MSIH-VECM model by allowing differing speeds of adjustment to equilibrium depending on whether interest rates are above or below equilibrium, i.e. whether the $\boldsymbol{\beta}^{'}\mathbf{y}_{t-1}$ is negative or positive. We can enrich the models considered by Clarida et al. (2006) by allowing regime dependent behavior for speed of adjustment and the autoregressive coefficients (or short-run parameters), hence we retain the usual assumption by assuming the long-run parameters contained in the cointegration vector $\boldsymbol{\beta}$ are regime-invariant.

$$\Delta\mathbf{y}_t = \mathbf{v}(s_t) + \boldsymbol{\Psi}_t\boldsymbol{\alpha}^{+}(s_t)\boldsymbol{\beta}^{'}\mathbf{y}_{t-1} + (\mathbf{I}-\boldsymbol{\Psi}_t)\boldsymbol{\alpha}^{-}(s_t)\boldsymbol{\beta}^{'}\mathbf{y}_{t-1} + \sum\nolimits_{i=1}^{p}\boldsymbol{\Gamma}_i(s_t)\Delta\mathbf{y}_{t-i} + \boldsymbol{\varepsilon}_t \qquad (4)$$

Where $\mathbf{I}_t$ is a $r\times r$ identity matrix, and $\boldsymbol{\Psi}_t$ is a $r\times r$ diagonal matrix whose jth diagonal at time *t* taking the value of unity or zero according to whether the lagged jth deviation from the equilibrium, i.e. the jth element of $\boldsymbol{\beta}'\mathbf{y}_{t-1}$ is positive or negative respectively. This model can be noted as Markov-switching-intercept-autoregressive-heteroskedastic (MSIAH) Asymmetric VECM.

In forecasting exercises provided in Section 4 we concentrate the following 9 models outlined in Table 1 in addition to Random Walk (RW) model which constitutes one of the benchmark models.

Table 1 is about here

Estimation of MSIAH-VECM models can be carried out in two steps as suggested by Krolzig (1996), and as applied, among others, by Clarida et. al. (2003, 2006), Krolzig (2002). First, cointegration tests and the estimation of the parameters of the long-run relations can be accomplished by the maximum likelihood (ML) approach to the problem of estimation and hypothesis testing in the context of VECMs as outlined in Johansen's (1991, 1996). Second step, the long-run parameter matrix, $\boldsymbol{\beta}$ estimated (and identified) in the first step is embedded in the above MS-VECMs. Then, the remaining parameters can be estimated by using the expectation maximization algorithm as in Krolzig (1996).

3. Long Run Equilibrium Relationship and term structure of interest rates

3.1 Data and Time Series Properties

In this section we analyze the time series properties of the variables that are included in our analysis[4]. We use weekly data covering the period 1993w1-2009w5 for interest

[4] This is important for us since the multivariate cointegration test applied here requires that variables are firmly established as I(1).

rates at 90, 120, 180, 270 and 360 days maturities: $R_{90}, R_{120,} R_{180,} R_{270}, R_{360}$ [5]. As interest rates we use Treasury bond rates with maturities 90, 120, 180, 270 and 360 days. These data are obtained from Istanbul Stock Exchange database on a daily basis[6] and weekly averages are used in the estimation. In order to proceed with the co-integration analysis, we first test for presence of unit roots with different unit root tests and conclude that all interest rate series are I(1)[7].

3.2. Cointegration Tests and Long-Run Identification

As mentioned above, in the first stage of our estimation process, we work in a symmetric linear VAR model in levels (i.e. Equation (3) with $M = 1$) to accomplish our cointegration analysis within the Johansen's framework. Prior to cointegration tests, the decision about the lag length (*p*) of underlying (linear) vector autoregressive (VAR) model must be accomplished. However, as is well known (e.g. Cheung and Lai (1993) Johansen's cointegration tests are rather sensitive to different parameterizations in the lag length. Therefore we report the results for different lag specifications up to 6 lags. It should be mentioned that the results outlined below is highly robust to higher lag orders of the VAR model. When these tests are performed, the intercept term is constrained

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[5] In fact, we first perform the following transformation to our data: $R = \ln(1+i)$, where i is the interest rate.

[6] The interest rate data has been obtained by Riskturk (www.riskturk.com). In constructing the yield curve official bond market data has been collected from Istanbul Stock Exchange. Since the Turkish Fixed Income Bill and Bonds are traded in an official exchange (more information can be found at www.ise.org) a reliable official data exists and the market is rather liquid for an emerging market. Once the official data is obtained from the ISE, the spot yields are solved. We used two alternative yield curve methodologies to construct weekly static yield curves which are namely linear interpolation and Nelson and Siegel (1987) nonlinear method. However, we could only construct the yield curve via Nelson Siegel only post 2000 period. This is because, before 2000 there were very few bond prices available and constructing a nonlinear yield curve with 3-4 bonds was not feasible. We compared the results obtained by these two methods. Results obtained from these two methods were qualitatively the same. We only present the results wıth linear scheme. Both the curves and the results can be shared upon request.

[7] We do not report these results to save space. They are available upon request.

into cointegration space. Since as mentioned above, the level variables are not trended, this formulation ensures that the solution of the model in terms of level variables does not contain linear trends[8].

Trace statistics[9], reported in Table 2, indicate that the interest rate series are cointegrated with the co-integration vector dimension of 4. In other words we conclude that the interest rate series have a long run equilibria with a co-integration dimension of 4 out of five variables (i.e. $r = 4$)[10]. This finding is consistent with the EH hypothesis which suggests that interest rates with various maturities should move together in the long run.

Table 2 is about here

We also wish to test whether the over-identifying restrictions imposed by EH can be supported by the data. More specifically, EH, as outlined above, implies the following 4 over-identifying restrictions on $\boldsymbol{\beta}$ matrix:

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[8] We think the cointegration vectors should not contain a constant term,. Therefore we further test whether intercept terms to be equal to zero or not.

[9] We only report trace statistics as suggested by Cheung Lai (1993). The computations in this section are carried out by using CATS Version 2. MS VECM models are estimated by using the GAUSS routine, MSVARlib, developed by Benoit Bellone (http://bellone.ensae.net/MSVARlib.html). The codes for remaining calculations, forecasts and forecasts test statistics, are written in GAUSS. Our GAUSS code and data are available upon request

[10] Small sample corrected trace test statistics (Trace * statistics) of Johansen (2002) are qualitatively indicate the same result.

$$\boldsymbol{\beta}'\mathbf{y}_t = \begin{bmatrix} -1 & 1 & 0 & 0 & 0 & 0 \\ -1 & 0 & 1 & 0 & 0 & 0 \\ -1 & 0 & 0 & 1 & 0 & 0 \\ -1 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R_{90,t} \\ R_{120,t} \\ R_{180,t} \\ R_{270,t} \\ R_{360,t} \end{bmatrix}$$

The resulting Likelihood ratio (LR) test has a chi-square value $\chi(8) = 79.868$[11] which leads the rejection of these over-identifying restrictions with an associated p-value of 0.000. However, Johansen (2000) argues LR tests over-reject over identifying restrictions and suggests a Barlett correction factor to overcome this problem. If we use correction we obtain an LR statistic that is equal to $\chi(8) = 9.509$ together with a p-value 0.301. The underlying correction factor is equal to 8.399. Therefore the restrictions implied by EH hypothesis cannot be rejected by the data at any conventional significance levels. These cointegration relations, i.e. spreads, can be followed from Figure .1 Error corrections asymmetries, mentioned above, can be easily observed in this figure.

Figure 1 is here

3.2. Tests of Asymmetry and Linearity

As we have shown that interest rate series have long run equilibrium, it is interesting to investigate the short run dynamic adjustments. One major question regarding the term structure modeling is whether the short run error dynamics exhibit an asymmetric pattern. In other words, what we wish to distinguish is whether the sign of the shock causes a different adjustment speed towards the equilibrium. One may expect that the

[11] The degrees of freedom is equal to 8 since we also restrict all the 4 intercepts to be equal to zero as is mentioned above.

negative shocks might take longer to adjust than that of positive shocks. In this subsection we test the error correction asymmetries (III, VIII and IX in Table 1) against their symmetric alternatives (see Table 3 below), by using LR tests. Similarly, we test our five nonlinear models against their relevant linear alternatives. All LR tests indicate that both asymmetries are nonlinearities are present in the data and asymmetric MSIAH VECM should be the preferred model as it holds the highest LR test statistics.

Table 3 is here

As discussed before Turkish interest rates do exhibit serious nonlinearity and our tests confirm this. There were various crisis and recessions which changed the linear relationship among interest rates. Particularly, the following years: 1994, 1997, 2001 and 2008 are the crisis periods which led the linear relationships to break down. In addition, Turkish interest rate data do show asymmetries in interest rate spread adjustments. As we experienced, yield curve twists usually coincide with recessions whereas large term spreads are generally indicative of expansion. Usually, negative term spreads generally show fast correction whereas large yield spreads do have a slower correction. These type of adjustments are asymmetric in nature and can be better modeled via asymmetric time series approaches. Our findings here confirm this empirical fact.

4. Forecasting the Term Structure of Interest Rates out of Sample with MSIAH VECMs

The approach developed by Krolzig (1996, 2002) is used to predict multiple time series subject to Markovian shifts in the regime. The k-step ahead predictor for symmetric MSIH-VECM in (5) is given by

$$E\left(\Delta\mathbf{y}_{t+k} \middle| \Delta\mathbf{y}_t, ..., \Delta\mathbf{y}_0\right) = \mathbf{MP}^k \hat{\boldsymbol{\xi}}_{t|t} + \mathbf{NP}^k \hat{\boldsymbol{\xi}}_{t|t} \boldsymbol{\beta}' \mathbf{y}_{t-1} + \sum\nolimits_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta\mathbf{y}_{t-i}$$

(5)

Where $\mathbf{M} = \left[\mathbf{v}_1 : ... : \mathbf{v}_M\right]$ and $\mathbf{N} = \left[\boldsymbol{\alpha}_1 : ... : \boldsymbol{\alpha}_M\right]$. $\mathbf{P}$ is the transposed matrix of transition probabilities, $\hat{\boldsymbol{\xi}}_{t|t}$ is the vector of filtered regime probabilities at time *t*. The forecast for the other models can be constructed in similar manners.

The out-of-sample forecasts for a given horizon k are constructed by using (5). The coefficients in (4) are estimated by running regressions with data up through the date $t_0 < T$. The first k-horizon forecast is obtained by using the coefficient estimates from this first regression. Next, the time subscript is advanced, and the procedure is repeated for $t_0 + 1$, $t_0 + 2, \ldots, T - k$ to obtain $N_f = T - t_0 - k + 1$ k-step distinct forecasts[12]. By using these N_f k-horizon forecasts we evaluate the forecasting performance our models by using Root Mean Square Error (RMSE)[13].

[12] The number forecasts differs between 89 and 37 for different k values between 1 and 52
[13] We also use Mean Absolute Error (MAE) in all the forecasting and forecast evaluation procedures that we use in this paper. To save the space we only report the results associated with RMSE. The results are qualitatively identical with MAE. They are available upon request.

In Table 4 we report the average of RMSE over N_f (number of forecasts at k-horizon) and over n variables (5 interest rates at different maturities).

Table 4 is here

The table compares different models at different forecast horizons (k). The emboldened numbers show the smallest of the RMSEs, therefore the best model, at the corresponding forecast horizon (k). The table reveals the fact that the symmetric MSIAH-VAR is the "best" model in terms of forecast accuracy at all horizons.

4.1 Assessing the forecast accuracy: Diebold and Mariano test

In order to assess the relative accuracy of forecasts derived from two competing models, we first employ the Diebold and Mariano (1995) which is used to compare, say model *l*, with a benchmark. The null hypothesis is that the model *l*, is no better than benchmark against alternative of the model *l*, being superior than benchmark [14]We first use Random Walk (RW), then the best model as our benchmarks.

Table 5 is here

The results on DM statistics displayed in Table 5 indicate that all models outperform RW except first horizon On the other hand, the second panel of the table indicates that

[14] In the previous version of the paper the null hypothesis used is that the benchmark is no better than model *l*.

there is no model outperforming our best MS model. To account for possible data snooping bias we use White (2000)'s method

4.2 Assessing the forecast accuracy: Reality Check

White (2000) developed an elegant test of superior unconditional predictive ability among multiple models built on Diebold and Mariano (1995) and West (1996). We report the results on White (2000) test in Table 6 where Prc1 is the bootstrap reality check p-value for comparing the model *l*, with the benhmark model (like DM test), and Prc2 is the bootstrap p-value for comparing the best of *l* models with the benchmark model. The first number for Prc2 is the bootstrap p-value for the null hypothesis that the best of the first *l* models is no better than the benchmark. The last number for Prc2 checks if the best of all the models under comparison has no superior predictive ability over the benchmark model. Reality check results confirm the results obtained in DM case.

We, then, divide our data into two sub-periods (1993w1-2000w52 and 2002w1-2009w5) and repeat the above analysis. The second period corresponds to the beginning inflation targeting regime and much stable economy together with considerably low inflation rates[15]. In general, RW are beaten, MS models perform better than the others as above and there are some evidence on that assymetries help to increase predictive powers of our models in post 2002 period. Therefore we conclude that regime switching models have better predictive powers for the weekly interests rates.

[15] We do not report these results here to save space They are available upon request. The crisis period of 2001 is excluded from the analysis.

Table 6 is here

4.3 Comments on Empirical Findings

We can summarize our findings as follows. First we observe a long run relationship in the interest rate data. We show that interest rates with different maturities are moving together in the long run. This finding is in line with the predictions of expectations theory. Furthermore, the dynamics of these interest rate series can be better modeled in a non-linear environment. For instance, nonlinear time series model fits the data better than that of linear benchmark models. This may be expected since the economy faces different growth and inflationary states, a regime switching model can mimic interest rates data more successfully. As we discussed before, in-sample data confirms the existence of asymmetry in the short run adjustments in interest rates. This is rather logical since negative spreads (i.e. shocks for the twisted yield curve) may have a different adjustment speed than that of positive spread shock. Since negative term spread usually implies crash or crisis corrections take place very fast. However, positive term spread may take a longer adjustment period. This is rather important finding and confirmed with the in sample data. This asymmetry property, which can be clearly seen from Figure 1 above, has important implications for the monetary policy and credibility. However, the is little evidence on that the asymmetric aspect of this model has any impact on the predictive power for the interest rates which may be related to the fact that in the recent years Turkish interest rates do not exhibit asymmetric effects because of recent disinflationary period. So forecasting experiment might not be successful. In any case, we need to conclude that, unlike Clarida et al (2006), we cannot obtain forecasting gains via asymmetric models in our data set.

5. Conclusion

In this paper we study the nonlinearity and asymmetry in the weekly Turkish interest rates. The interest rate data with various maturities move together which is in line with the predictions of the expectations hypothesis theory. In addition, we also show that the interest rate data exhibits nonlinear time series properties. Both in the in-sample and out of sample data, we demonstrate that nonlinear regime switching models have better predictive power. However, we cannot reach a decisive conclusion regarding the forecasting power based on asymmetric econometric models of our interest rate data. In addition, in recent years, Turkish Treasury has successfully increased the maturity of government bonds. Studying the terms structure of interest rates with longer maturity and linking the term structure with macroeconomic factors is left for future research.

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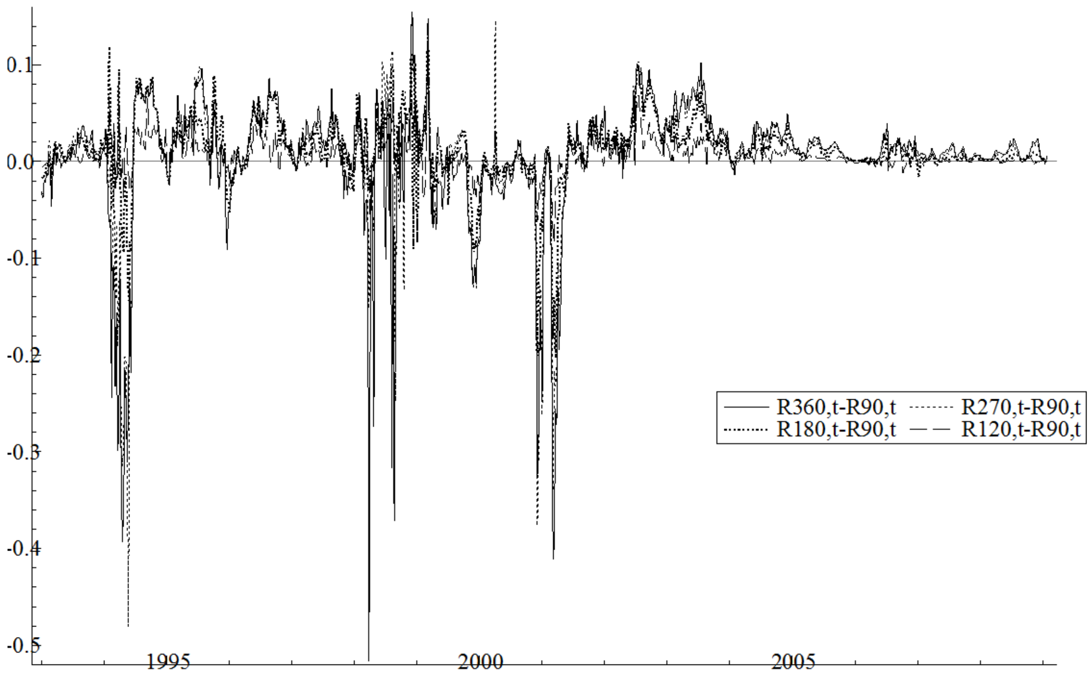
Figures:

Figure 1: Spreads



Tables:

Table 1 Models used in Forecasting

(I)	Linear Symmetric VAR, i.e. (3) with $M = 1$ and $\boldsymbol{\beta} = \mathbf{0}$
(II)	Linear Symmetric VECM, i.e. (3) with $M = 1$
(III)	Linear Asymmetric VECM, i.e. (4) with $M = 1$ and $\boldsymbol{\Psi}_t = \mathbf{I}$
(IV)	MSIH Symmetric VAR, i.e. (3) with $\boldsymbol{\beta} = \mathbf{0}$
(V)	MSIAH Symmetric VAR, i.e. (4) with $\boldsymbol{\beta} = \mathbf{0}$
(VI)	MSIH Symmetric VECM, i.e. (3)
(VII)	MSIAH Symmetric VECM, i.e. (4) with $\boldsymbol{\Psi}_t = \mathbf{I}$
(VIII)	MSIH Asymmetric VECM, i.e. (4) with $\boldsymbol{\alpha}(s_t) = \boldsymbol{\alpha}; \boldsymbol{\Gamma}(s_t) = \boldsymbol{\Gamma}$
(IX)	MSIAH Asymmetric VECM, i.e. (4)

Table 2: Cointegration Rank Statistics (Trace Statistics)

H_0	H_1	VAR (1)	VAR (2)	VAR (3)	VAR (4)	VAR(5)	VAR(6)
r = 0	r ≥ 1	1111.028 (0.000)	711.115 (0.000)	566.529 (0.000)	467.667 (0.000)	421.127 (0.000)	380.881 (0.000)
r ≤ 1	r ≥ 2	675.351 (0.000)	429.186 (0.000)	301.664 (0.000)	235.302 (0.000)	242.769 (0.000)	219.308 (0.000)
r ≤ 2	r ≥ 3	336.036 (0.000)	228.539 (0.000)	146.009 (0.000)	133.126 (0.000)	129.978 (0.000)	125.420 (0.000)
r ≤ 3	r ≥ 4	82.944 (0.000)	74.651 (0.000)	52.540 (0.000)	52.134 (0.000)	50.656 (0.000)	55.603 (0.000)
r ≤ 4	r ≥ 5	2.689 (0.646)	2.656 (0.656)	2.196 (0.738)	1.951 (0.783)	1.948 (0.784)	2.049 (0.765)

Note: p-values are given parentheses.

Table 3: Asymmetry and Linearity Tests

a) Asymmetry Tests

$H_0 \downarrow$ \ $H_1 \rightarrow$	**Linear Asymmetric VECM**	**MSIH Asymmetric VECM**	**MSIAH Asymmetric VECM**
Linear Symmetric VAR	805.267	3114.302	3201.502
Linear Symmetric VECM	140.892	2449.928	2537.128
MSIH Symmetric VAR		318.842	406.042
MSIAH Symmetric VAR			305.941
MSIH Symmetric VECM		133.423	220.623
MSIAH Symmetric VECM			96.833

b) Linearity Tests

$H_0 \downarrow$ \ $H_1 \rightarrow$	**MSIH Symmetric VAR**	**MSIAH Symmetric VAR**	**MSIH Symmetric VECM**	**MSIAH Symmetric VECM**	**MSIH Asymmetric VECM**	**MSIAH Asymmetric VECM**
Linear Symmetric VAR	2795.459	2895.560	2980.878	3104.668	3114.302	3201.502
Linear Symmetric VECM			2316.504	2440.294	2449.928	2537.128
Linear Asymmetric VECM					2309.035	2396.235

Note: LR is likelihood ratio tests of the linearity null hypothesis are indicated in cells, where the unrestricted and restricted models being tested are indicated in columns and rows respectively. The tests are constructed as $2(\ln L^* - \ln L)$, where L^* and L represent the unconstrained and the constrained maximum log likelihood respectively. These test statistics are asymptotically distributed as $\chi(g)$ under the null hypotheses, where n is the number of restrictions. We do not report p-values since they all are very close to 0.

Table 4: Forecast Accuracies of Different Models (RMSE)

H	Linear Sym VAR	Linear Sym VECM	Linear Asy VECM	MSIH Sym VAR	MSIAH Sym VAR	MSIH Sym VECM	MSIAH Sym VECM	MSIH Asy VECM	MSIAH Asy VECM	RW
1	0.29138	0.38243	0.30934	0.28232	**0.27765**	0.28467	0.28692	0.29718	0.29380	0.32650
2	0.31454	0.41523	0.32930	0.31193	**0.30906**	0.31680	0.33228	0.33393	0.32468	0.65162
4	0.33082	0.40946	0.33756	0.33197	**0.32906**	0.33858	0.36380	0.36509	0.34153	0.71635
12	0.35362	0.38973	0.36592	0.35419	**0.34913**	0.37109	0.39693	0.38542	0.38141	0.76059
24	0.33243	0.34974	0.36580	0.33266	**0.32727**	0.35431	0.37593	0.38950	0.35371	1.20447
36	0.32586	0.33678	0.34400	0.32602	**0.32012**	0.35399	0.36896	0.39133	0.33764	1.20845
48	0.33176	0.33815	0.34501	0.33178	**0.32548**	0.36063	0.37294	0.39808	0.33987	1.24738
52	0.33660	0.34191	0.35008	0.33660	**0.33054**	0.36547	0.37737	0.40350	0.34556	1.24589

Note: *h* is the forecast horizon. RMSE is given by. $RMSE = \sqrt{\frac{1}{k}\sum_{i=1}^{k}\left(y_{t+i} - \hat{y}_{t+i}\right)^2}$. Where $\hat{y}_{t+i}$ is the i period-ahead forecast of y_{t+i} .

Table 5: *p*-values of Diebold-Mariano (DM) statistics (RMSE)

(I) Benchmark: Random Walk

h	Linear Sym VAR	Linear Sym VECM	Linear Asym VECM	MSIH Sym VAR	MSIAH Sym VAR	MSIH Sym VECM	MSIAH Sym VECM	MSIH Asym VECM	MSIAH Asym VECM
1	0.3619	0.7262	0.4318	0.3264	0.3090	0.3365	0.3393	0.3855	0.3686
2	0.0000	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000
4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
24	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
36	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
48	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
52	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

(II) Benchmark: MSIAH Sym VAR

h	Linear Sym VAR	Linear Sym VECM	Linear ASym VECM	MSIH Sym VAR	MSIH Sym VECM	MSIAH Sym VECM	MSIH ASym VECM	MSIAH ASym VECM	Random Walk
1	0.8842	1.0000	0.9895	0.8007	0.8637	0.9036	0.9185	0.9386	0.6910
2	0.7903	1.0000	0.9833	0.8014	0.9457	0.9988	0.9392	0.9111	1.0000
4	0.9111	0.7265	1.0000	0.8963	0.9002	0.9774	0.9995	0.9877	1.0000
12	0.8510	0.9982	1.0000	0.9823	0.9990	1.0000	1.0000	0.9930	1.0000
24	0.9988	1.0000	0.9993	0.9993	1.0000	1.0000	1.0000	0.9856	1.0000
36	1.0000	1.0000	0.9895	1.0000	1.0000	1.0000	1.0000	0.9607	1.0000
48	1.0000	1.0000	0.9974	1.0000	1.0000	1.0000	1.0000	0.9926	1.0000
52	1.0000	1.0000	0.9993	1.0000	1.0000	1.0000	1.0000	0.9970	1.0000

Note: *h* is the forecast horizon. DM statistics is given as $DM = \bar{d} / \sqrt{LRV_{\bar{d}} / N_f}$. Where $\bar{d}$ is an average (over N_f observations) of the loss differential function of the RMSE, and $LRV_{\bar{d}}$ is a consistent estimate of the asymptotic variance the loss differential function, which is defined as $LRV_{\bar{d}} = \gamma_0 + 2\sum_{j=1}^{\infty} \gamma_j$, where $\gamma_j = \mathrm{cov}(d_t, d_{t-j})$. In the table we report the results associated with $j = 5$. The qualitatively similar results are obtained with the smaller *j*s.

Table 6: *p*-values of Reality Check statistics (RMSE)

(I) Benchmark: Random Walk

h	Prc	Linear Sym VAR	Linear Sym VECM	Linear Asym VECM	MSIH Sym VAR	MSIAH Sym VAR	MSIH Sym VECM	MSIAH Sym VECM	MSIH Asym VECM	MSIAH Asym VECM
1	Prc 1	0.280	0.807	0.383	0.240	0.221	0.254	0.251	0.328	0.304
	Prc 2	0.288	0.311	0.321	0.276	0.258	0.259	0.260	0.268	0.272
2	Prc 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Prc 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	Prc 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Prc 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12	Prc 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Prc 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
24	Prc 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Prc 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
36	Prc 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Prc 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
48	Prc 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Prc 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
52	Prc 1	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Prc 2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

(II) Benchmark: MSIAH Sym VAR

h	Prc	Linear Sym VAR	Linear Sym VECM	Linear Asym VECM	MSIH Sym VAR	MSIH Sym VECM	MSIAH Sym VECM	MSIH Asym VECM	MSIAH Asym VECM	Random Walk
1	Prc 1	0.918	1.000	0.995	0.819	0.904	0.946	0.945	0.910	0.777
	Prc 2	0.916	0.960	0.971	0.912	0.796	0.840	0.889	0.925	0.956
2	Prc 1	0.837	1.000	0.994	0.841	0.977	1.000	0.977	0.935	1.000
	Prc 2	0.833	0.935	0.955	0.944	0.859	0.876	0.936	0.949	0.963
4	Prc 1	0.725	1.000	0.957	0.959	0.999	1.000	1.000	0.929	1.000
	Prc 2	0.716	0.833	0.885	0.938	0.841	0.850	0.944	0.953	0.961
12	Prc 1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Prc 2	1.000	1.000	1.000	1.000	0.933	0.947	0.969	0.976	0.977
24	Prc 1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Prc 2	1.000	1.000	1.000	1.000	0.937	0.944	0.953	0.961	0.962
36	Prc 1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000
	Prc 2	1.000	1.000	1.000	1.000	0.925	0.933	0.945	0.952	0.956
48	Prc 1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Prc 2	1.000	1.000	1.000	1.000	0.867	0.875	0.902	0.910	0.916
52	Prc 1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Prc 2	1.000	1.000	1.000	1.000	0.835	0.846	0.876	0.891	0.898

Note: *h* is the forecast horizon. The numbers on the rows of Prc1 and Prc2 are the bootstrap reality check *p*-values.