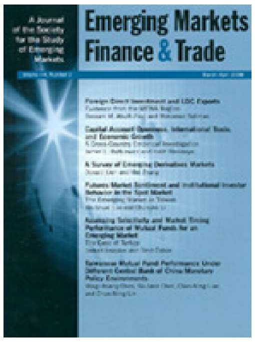

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The Role of Regime Shifts in the Term Structure of Interest Rates: Further Evidence from an Emerging Market

Burak Saltoglu and M. Ege Yazgan

ABSTRACT: In this paper, we investigate the interrelationships among Turkish interest rates having different maturities by using a regime-switching vector error correction model. We find a relationship of long-run equilibrium among interest rates having various maturities. Furthermore, we conclude that term structure dynamics exhibit significant nonlinearity. A forecasting experiment also reveals that the nonlinear term structure models fare better in forecasting than other linear specifications. However, we cannot conclude that interest rate adjustments are made in an asymmetric way in the long run.

KEY WORDS: cointegration, forecast evaluation, forecasting, regime switching, term structure of interest rates.

Studies on term structure dynamics have always been at the core of macroeconomics and finance research. Campbell and Clarida (1987), Campbell and Shiller (1991), and Hall et al. (1992) studied the long-run dynamics of the term structure of interest rates. Recently, Diebold and Li (2006) extended the popular static yield curve model developed by Nelson and Siegel (1987). With an innovative structure, Diebold and Li (2006) enabled researchers to forecast interest rates using linear models. Two improved versions of this structure are presented in Diebold et al. (2008, 2011). Recently, Clarida et al. (2006) proposed a nonlinear multivariate vector error correction model (VECM) 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 have addressed the dynamics of the term structure of interest rates in emerging markets.[1] However, none of these studies, except the study of Brazil by Guillen and Tabak (2008), explicitly address the nonlinearity of the term structure of interest rates. During the past two decades, the Turkish economy has experienced a number of sharp downturns and economic crises,[2] which have had a direct impact on interest rates and the term structure of interest rates. As a result, the term structure dynamics of the Turkish economy can be better investigated under nonlinear models. The Turkish economy has experienced long high inflationary period during the past three decades with inflation rates being around double or even triple digit levels in some periods. The inflation rates were managed to be lowered around 10 percent or lower as late as from 2004 onward. However, from time to time Turkish policymakers wanted to halt hyperinflation via various tools. So the economy had high and low inflationary periods with very high and relatively milder interest rates. Therefore, nonlinearity is a

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necessary aspect of modeling in the Turkish interest rate markets. Moreover, it is also interesting to see whether the short-run adjustments toward equilibrium are symmetric or not. It is important to compare the speed of adjustment toward equilibrium when inflation is relatively high with that of when it is low. In other words, if the inflationary expectations hit a positive shock, how quickly can this shock be dissipated and how does that compare with the speed of dissipating a negative inflationary shock? This asymmetry has important implications for central banks setting monetary policy that need to be investigated.

This paper seeks 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 Turkish interest rates using different maturities. In addition to these experiments, 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 expectations hypothesis (see below). We also demonstrate that there exists a nonlinear regime-switching structure in the weekly interest rate data we study. Finally, we show that negative and positive interest rate 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 the central bank. Furthermore, negative spreads between long and short maturity of interest rates are usually very rare in the Turkish data (see Figure 1). But negative spreads usually predate crises and recessions. Therefore, negative spreads and shocks tend to be shorter lived than positive spreads. Our findings on asymmetry are therefore in line with the empirical facts of the Turkish economy. However, forecasts generated by symmetric nonlinear regime-switching models were more accurate than those generated by linear vector time-series models. This result suggests that an asymmetric adjustment in the interest rates occurs but this is not strong enough to accurately predict the interest rates. This may be related to the fact that our forecasting exercise was conducted without sufficient asymmetrical data. Therefore, even though we can capture asymmetry in the data, this is not useful for forecasting. To the best of our knowledge, this is the first comprehensive attempt to analyze the term structure dynamics of an emerging market economy. Our research may have some important implications for the Turkish economy. First, as 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 implications for monetary policy.

Cointegration and the Expectations Hypothesis

The expectations hypothesis can be formulated as follows (Campbell and Shiller 1991; Clarida et al. 2006):

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

where $R_{k,t}$ is the yield to maturity obtained from a k-period pure discount bond. This equation can be stated as: the longer-term spot rate is equal to the average expected

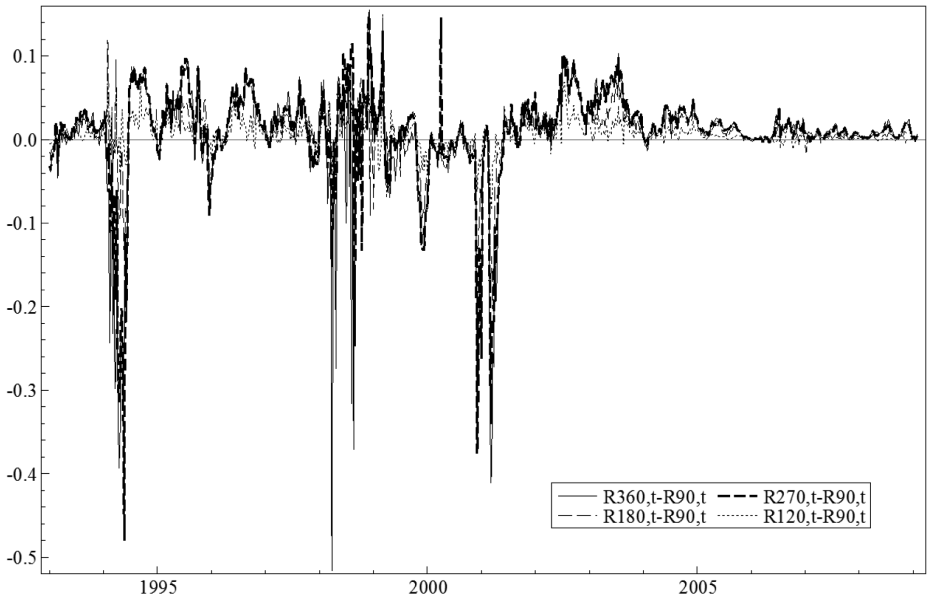

Figure 1. Spreads

Note: R360,t-R90,t; R270,t-R90,t; R180,t-R90,t; R120,t-R90,t refer to the spreads between 360, 270, 180, and 120 days maturity interest rates and 90 days maturity interest rate.

short-term interest rates. If we subtract $R_{1,t}$ from both sides of Equation (1), we obtain the following equation:

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

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

Modeling Term Structure Nonlinearities Using a Regime-Switching Vector Error Correction Model

The 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 (1989) and 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:

$$\Delta y_t = \nu(s_t) + \alpha\beta' y_{t-1} + \Sigma_{i=1}^{p}\Gamma_i \Delta y_{t-i} + \varepsilon_t, \tag{3}$$

where 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 y contains interest rates maturing at 90, 120, 180, 270, and 360 days, that is, $y_t = (R_{90,t}, R_{120,t}, R_{180,t}, R_{270,t}, R_{360,t})$. The $n \times r$ order α and β matrices contain the factor-loading (or speed of adjustment) and cointegration vectors, where r is the number of cointegrating vectors. ν is the vector of intercepts, $\Gamma_1, \ldots, \Gamma_p$ are the matrices containing the autoregressive parameters, and ε_t is a white noise vector process such that $\varepsilon_t | s_t \sim NID\,(0, \Sigma(s_t))$. The regime-generating process is assumed to be an ergodic Markov chain with a finite number of states $s_t \in [1, \ldots, M]$ governed by transition probabilities $p_{ij} = \Pr(s_{t+1} = j / s_t = i)$ and $\Sigma_{j=1}^{M} p_{ij} = 1$ for all $i, j \in \{1, \ldots, M\}$. This type of MS VECM model, which allows regime shifts both in intercept[3] and in variance and covariance matrices, is called a Markov-switching-intercept-heteroskedastic-VECM (MSIH-VECM), following 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 the interest rates are above or below the equilibrium, that is, whether the $\beta' y_{t-1}$ is negative or positive. We can enrich the models considered by Clarida et al. (2006) by allowing speed of adjustment and the autoregressive coefficients (or short-run parameters) to be regime dependent. We retain the usual assumption by assuming that the long-run parameters contained in the cointegration vector β are regime invariant.

$$\Delta y_t = \nu(s_t) + \Psi_t \alpha^{+}(s_t)\beta' y_{t-1} + (I_t - \Psi_t)\alpha^{-}(s_t)\beta' y_{t-1} + \Sigma_{i=1}^{p}\Gamma_i(s_t)\Delta y_{t-1} + \varepsilon_t, \tag{4}$$

where I_t is an $r \times r$ identity matrix, and Ψ_t is an $r \times r$ diagonal matrix whose jth diagonal at time t, taking the value of one or zero, respectively, according to whether the lagged jth deviation from the equilibrium, that is, the jth element of $\beta' y_{t-1}$, is positive or negative. This model can be called a Markov-switching-intercept-autoregressive-heteroskedastic (MSIAH) asymmetric VECM.

In the forecasting exercises provided below, we employ the nine models outlined in Table 1 in addition to the random walk model, which constitutes one of the benchmark models.

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) and Krolzig et al. (2002). First, cointegration tests and the estimation of the parameters of the long-run relationships can be accomplished using the maximum likelihood (ML) approach to the problem of estimation and hypothesis testing in the context of VECMs, as outlined in Johansen (1996). Second, the long-run parameter matrix, β, estimated (and identified) in the first step, is embedded into the above MS-VECMs. Then, the

Table 1. Models used in forecasting

(I) Linear symmetric VAR: (3) with $M = 1$ and $\beta = 0$
(II) Linear symmetric VECM: (3) with $M = 1$
(III) Linear asymmetric VECM: (4) with $M = 1$ and $\Psi_t = I$
(IV) MSIH symmetric VAR: (3) with $\beta = 0$
(V) MSIAH symmetric VAR: (4) with $\beta = 0$
(VI) MSIH symmetric VECM: (3)
(VII) MSIAH symmetric VECM: (4) with $\Psi_t = I$
(VIII) MSIH asymmetric VECM: (4) with $\alpha(s_t) = \alpha$; $\Gamma(s_t) = \Gamma$
(IX) MSIAH asymmetric VECM: (4)

remaining parameters can be estimated by using the expectation maximization algorithm, as in Krolzig (1996).

Long-Run Equilibrium Relationship and the Term Structure of Interest Rates

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

Cointegration Tests and Long-Run Identification

As mentioned above, in the first stage of our estimation process, we work in a symmetric linear vector autoregressive (VAR) model in levels (i.e., Equation (3) with $M = 1$) to accomplish our cointegration analysis within Johansen's framework. Prior to the cointegration tests, the decision about the lag length (p) of the underlying (linear) VAR model must be accomplished. However, as is well known (see, 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 six lags. It should be mentioned that the results outlined below are highly robust to higher lag orders of the VAR model. When these tests are performed, the intercept term is constrained 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 cointegration vector dimension of 4. In other words, we conclude that the interest rate series have long-run equilibria with a cointegration dimension of four out of five variables (i.e., $r = 4$).[10] This finding is consistent with the expectations hypothesis,

Table 2. Cointegration rank statistics (trace statistics)

H_0	H_1	VAR (1)	VAR (2)	VAR (3)	VAR (4)	VAR (5)	VAR (6)
$r = 0$	$r \geq 1$	1,111.028	711.115	566.529	467.667	421.127	380.881
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r \leq 1$	$r \geq 2$	675.351	429.186	301.664	235.302	242.769	219.308
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r \leq 2$	$r \geq 3$	336.036	228.539	146.009	133.126	129.978	125.420
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r \leq 3$	$r \geq 4$	82.944	74.651	52.540	52.134	50.656	55.603
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r \leq 4$	$r \geq 5$	2.689	2.656	2.196	1.951	1.948	2.049
		(0.646)	(0.656)	(0.738)	(0.783)	(0.784)	(0.765)

Note: p-values are in parentheses.

which suggests that interest rates that have different maturities should move together in the long run.

We also wish to test whether the overidentifying restrictions imposed by the expectations hypothesis is supported by the data. More specifically, the expectations hypothesis, as outlined above, implies the following four overidentifying restrictions on the β matrix:

$$\beta' y_t = \begin{bmatrix} -1 & 1 & 0 & 0 & 0 \\ -1 & 0 & 1 & 0 & 0 \\ -1 & 0 & 0 & 1 & 0 \\ -1 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R_{90,t} \\ R_{120,t} \\ R_{180,t} \\ R_{270,t} \\ R_{360,t} \end{bmatrix}.$$

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

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 adjustment toward equilibrium to occur at a different speed. One might expect that negative shocks require a longer period of adjustment than positive shocks do. In this subsection we test the error correction asymmetries (III, VIII, and IX in Table 1) against their symmetric alternatives (see Table 3) using LR tests. Similarly, we test our five nonlinear models against their relevant linear alternatives. All LR tests indicate that both asymmetries and nonlinearities are present in the data, and asymmetric MSIAH VECM should be the preferred model, as it contains the highest LR test statistics.

As discussed above, Turkish interest rates do exhibit serious nonlinearity and our tests confirm this fact. There were various crises and recessions, which changed the linear relationship among interest rates. In particular, the crises of 1994, 1997, 2001, and 2008 led the linear relationships to break down. In addition, Turkish interest rate data do show asymmetries in interest rate spread adjustments for the considered period. As is well known, yield curve twists usually coincide with recessions, whereas wide term spreads are generally indicative of expansion. Negative term spreads generally show fast correction, whereas wide yield spreads have a slower correction. These types of adjustments are asymmetric in nature and can be better modeled using asymmetric time-series approaches. Our findings here confirm this empirical fact.

Table 3. Asymmetry and linearity tests

Panel A: Asymmetry tests

	H_1		
H_0	Linear asymmetric VECM	MSIH asymmetric VECM	MSIAH asymmetric VECM
Linear symmetric VAR	805.267	3,114.302	3,201.502
Linear symmetric VECM	140.892	2,449.928	2,537.128
MSIH symmetric VAR		318.842	406.042
MSIAH symmetric VAR			305.941
MSIH symmetric VECM		133.423	220.623
MSIAH symmetric VECM			96.833

Panel B: Linearity tests

	H_1					
H_0	MSIH symmetric VAR	MSIAH symmetric VAR	MSIH symmetric VECM	MSIAH symmetric VECM	MSIH asymmetric VECM	MSIAH asymmetric VECM
Linear symmetric VAR	2,795.459	2,895.560	2,980.878	3,104.668	3,114.302	3,201.502
Linear symmetric VECM			2,316.504	2,440.294	2,449.928	2,537.128
Linear asymmetric VECM					2,309.035	2,396.235

Notes: The numbers in the cells are the LR (likelihood ratio) of the linearity null hypothesis obtained from the unrestricted and restricted models being tested. 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 hypothesis, where n is the number of restrictions. We do not report p-values since they all are very close to 0.

Forecasting the Term Structure of the Interest Rates of a Sample Using MSIAH VECMs

The approach developed by Krolzig and colleagues (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 is given by

$$E(\Delta y_{t+k} \mid \Delta y_t, \ldots, \Delta y_0) = MP^k \hat{\xi}_{t|t} + NP^k \hat{\xi}_{t|t} \beta' y_{t-1} + \Sigma_{i=1}^{p-1} \Gamma_i \Delta y_{t-i}, \tag{5}$$

where $M = [v_1 : \ldots : v_M]$ and $N = [\alpha_1 : \ldots : \alpha_M]$. P is the matrix of transition probabilities, and $\hat{\xi}_{t|t}$ is the vector of filtered regime probabilities at time t. The forecast for the other models can be constructed in a similar manner.

The out-of-sample forecasts for a given horizon k are constructed by using Equation (5). The coefficients in Equation (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] The N_f k-horizon forecasts are used to evaluate the forecasting performance of our models using the root mean square error (RMSE) criterion.[13] In Table 4 we report the average of RMSE over N_f (number of forecasts at k-horizon) and over n variables (five interest rates at different maturities).

Table 4 compares different models at different forecast horizons (k). The numbers in the MSIAH symmetric VAR column are the smallest RMSEs, indicating the best model at the corresponding forecast horizon (k). The table reveals that the symmetric MSIAH-VAR is the "best" model in terms of forecast accuracy at all horizons.

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) test (DM), which is used to compare a model (model l) with a benchmark. The null hypothesis is that the model l is no better than the benchmark against the alternative of the model l being superior than the benchmark.[14] We first use random walk, then the best model, as our benchmarks.

The results of the DM tests displayed in Table 5 indicate that all the models outperform random walk except first horizon. However, the second panel of the table indicates that there no model outperforms our best MS model. To account for possible data-snooping bias, we use White's (2000) method.

Assessing the Forecast Accuracy: Reality Check

White (2000) developed an elegant test of superior unconditional predictive ability compared to other models based on Diebold and Mariano (1995) and West (1996). We report the results on the White (2000) test in Table 6, where Prc1 is the bootstrap reality check p-value for comparing model l with the benchmark model (like a 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 whether the best of all the models under comparison has no predictive ability superior to the benchmark model. Reality check results confirm the results obtained in the DM case.

Table 4. Forecast accuracies of different models (RMSE)

h	Linear symmetric VAR	Linear symmetric VECM	Linear asymmetric VECM	MSIH symmetric VAR	MSIAH symmetric VAR	MSIH symmetric VECM	MSIAH symmetric VECM	MSIH asymmetric VECM	MSIAH asymmetric VECM	Random walk
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

Notes: h is the forecast horizon. RMSE is given by

$$\text{RMSE} = \sqrt{\frac{1}{k}\sum_{i=1}^{k}\left(y_{t+i} - \hat{y}_{t+i}\right)^2},$$

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)

Panel A: Benchmark: random walk

h	Linear symmetric VAR	Linear symmetric VECM	Linear asymmetric VECM	MSIH symmetric VAR	MSIAH symmetric VAR	MSIH symmetric VECM	MSIAH symmetric VECM	MSIH asymmetric VECM	MSIAH asymmetric 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

Panel B: Benchmark: MSIAH symmetric VAR

h	Linear symmetric VAR	Linear symmetric VECM	Linear asymmetric VECM	MSIH symmetric VAR	MSIH symmetric VECM	MSIAH symmetric VECM	MSIH asymmetric VECM	MSIAH asymmetric 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

Notes: h is the forecast horizon. DM statistics are given as

$$DM = \bar{d}\sqrt{\widehat{LRV}_{\bar{d}} / N_f},$$

where $\bar{d}$ is an average (over N_f observations) of the loss differential function of the RMSE, and $\widehat{LRV}_{\bar{d}}$ is a consistent estimate of the asymptotic variance of the loss-differential function, which is defined as $LRV_{\bar{d}} = \gamma_0 + 2\Sigma_{j=1}^{\infty}\gamma_j$, where $\gamma_j = \mathrm{cov}(d_t, d_{t-j})$. In the table we report the results associated with $j = 5$. Qualitatively similar results are obtained with a smaller j.

Table 6. *p*-values of reality check statistics (RMSE)

Panel A: Benchmark: random walk

h	Prc	Linear symmetric VAR	Linear symmetric VECM	Linear asymmetric VECM	MSIH symmetric VAR	MSIAH symmetric VAR	MSIH symmetric VECM	MSIAH symmetric VECM	MSIH asymmetric VECM	MSIAH asymmetric 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

(continues)

Table 6. Continued

Panel B: Benchmark: MSIAH symmetric VAR

h	Prc	Linear symmetric VAR	Linear symmetric VECM	Linear asymmetric VECM	MSIH symmetric VAR	MSIH symmetric VECM	MSIAH symmetric VECM	MSIH asymmetric VECM	MSIAH asymmetric 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

Notes: h is the forecast horizon. The numbers in rows Prc1 and Prc2 are the bootstrap reality check p-values.

We then divide our data into two subperiods (1993w1–2000w52 and 2002w1–2009w5) and repeat the above analysis. The second period corresponds to the beginning of the inflation-targeting regime and a much more stable economy with considerably lower inflation rates.[15] In general, the forecasting performance of random walks are poor, MS models perform better than the others as above, and there is some evidence that asymmetries help to increase the predictive power of our models in the post-2002 period. Therefore we conclude that the regime-switching models have better predictive powers for the weekly interest rates.

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 that have different maturities move 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 nonlinear environment. For instance, a nonlinear time-series model fits the data better than linear benchmark models do. This may be expected: since the economy goes through different growth and inflationary states, a regime-switching model can mimic interest rate data more successfully. As we discussed above, in-sample data confirms the existence of asymmetry in the short-run adjustments in interest rates. This is rather logical since negative spreads (the twisted yield curve) may have a different adjustment speed than that of positive spreads shock. Since a negative term spread usually implies crash or crisis, corrections take place very quickly. However, a positive term spread may require a longer adjustment period. This is a rather important finding and is confirmed with the in-sample data. This asymmetry property, which can be clearly seen from Figure 1, has important implications for monetary policy and credibility. However, there is little evidence that the asymmetric aspect of this model has any impact on its power to predict interest rates, which may be related to the fact that in recent years, Turkish interest rates have not exhibited asymmetric effects because of the recent disinflationary period. Hence, a forecasting experiment might not be successful. In any case, we must conclude that, unlike Clarida et al. (2006), we cannot obtain forecasting gains using asymmetric models with our data set.

Conclusion

In this paper we study the nonlinearity and asymmetry in the weekly Turkish interest rates. Interest rates that have different maturities move together, which is in line with the predictions of the expectations hypothesis. In addition, we show that the interest rate data exhibit nonlinear time-series properties. We demonstrate that nonlinear regime-switching models have better predictive power for both the in-sample and out-of-sample data. However, we cannot reach a decisive conclusion regarding the power of asymmetric econometric models to forecast interest rates. In addition, in recent years, the Turkish treasury has successfully increased the maturity of government bonds. Studying the term structure of interest rates with longer maturity periods and linking the term structure with macroeconomic factors is left for future research.

Notes

1. For instance, Alper et al. (2007) provided an analysis of the term structure of interest rates for Turkey. Telatar et al. (2003) examined the information content in the term structure of interest

rates about future inflation by using a time-varying parameter model. Kaya and Yazgan (2011) emphasized the effect of monetary policy change on the nature of this information content. See also Cuestas and Harrison (2010) and Gabrisch and Orlowski (2010).

2. See Yilmazkuday and Akay (2008) for a brief account of these developments and an analysis of business cycles of the Turkish economy in a regime-switching approach. See also Berument and Malatyali (2001).

3. Note that the intercept ν controls the mean of y_t through the relationship $\mu(s_t) = \nu(s_t)\{I - \Pi_1(s_t) - \ldots - \Pi_p(s_t)\}^{-1}$. An alternative representation is obtained by allowing the mean to vary with the state.

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

5. In fact, we first transform our data as follows: $R = \ln(1 + i)$, where i is the interest rate.

6. The interest rate data is obtained from Riskturk (www.riskturk.com). In constructing the yield curve official bond market data has been collected from the Istanbul Stock Exchange (ISE). Since the Turkish fixed income bills and bonds are traded on an official exchange (more information can be found at www.ise.org), 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: linear interpolation and the Nelson and Siegel (1987) nonlinear method. However, we could only construct the yield curve using the Nelson–Siegel method only in the 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 and found them to be qualitatively the same. We present only the results with a linear scheme. Both the curves and the results will be shared upon request.

7. In the interest of saving space, we do not report these results. They are available upon request.

8. We think the cointegration vectors should not contain a constant term. Therefore we further test whether intercept terms are equal to zero.

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

10. The small sample corrected trace test statistics (Trace * statistics) of Johansen (2002) qualitatively indicate the same result.

11. The degrees of freedom are equal to eight since we also restrict the value of all four intercepts to zero, as is mentioned above.

12. The number of forecasts differs, ranging between eighty-nine and thirty-seven for different k values between 1 and 52.

13. We also employ the mean absolute error (MAE) in all the forecasting and forecast evaluation procedures used in this paper. To save space, we report only the results associated with RMSE. The results are qualitatively identical with MAE. They are available upon request.

14. In a previous version of this paper, the null hypothesis was that the benchmark is no better than model l.

15. To save space we do not report these results here, but they are available from the authors upon request. The crisis period of 2001 is excluded from the analysis.

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