MODELING BUSINESS CYCLES WITH Markov Switching VAR MODEL: AN APPLICATION ON TURKISH BUSINESS CYCLES

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Abstract

In this paper, the Turkish Business Cycle characteristics were investigated via numerous univariate and multivariate Markov-switching specifications. By using Hamilton (1989) and Krolzig (1997) (MS-VAR) models, we examined the stochastic properties of the cyclical pattern of the quarterly Turkish real GNP between 1988-2002. The empirical analysis consists of mainly three parts. First, a large number of alternative specifications were tried and few were adopted with respect to various diagnostic statistics. Then, all selected models were tested agains their linear benchmarks. LR test results imply a strong evidence in favor of the nonlinear regime switching behavior. Furthermore, the multivariate specification with various macro aggregates and changing variance parameter outperformed the other MS models with reference to one-step ahead forecasting performance. With this specification, we can mimick the five recessionary periods experienced by the Turkish economy between 1988 and 2002. Finally, based on inference from this model a chronology of business cycle turning points was determined.

Keywords: Markov Switching Models, Business Cycles, MSVAR, Turkish Economy.

JEL Classifications: E32, C32.

1. INTRODUCTION

Research on business cycles has always been at the core of economic research agenda where one of the pioneering studies on the topic belongs to Burns and Mitchell (1946). This tradition has opened up two research areas namely, comovement among variables through the cycle, and the different behavior of the economy during different phases of the cycle. The first one gave rise to the formation of dynamic factor models and composition of indices.[1] The latter one inspired the use of nonlinear regime switching models with the seminal work of Hamilton (1989) that addressed whether the asymmetric movements occur systematically enough to be counted as part of the probabilistic structure of time series. The underlying idea was that business cycle expansions and contractions could be viewed as different regimes.[2] Two extensions of Hamilton (1989) model were Filardo (1994) and Diebold *et al* (1994). These models assume that the probability of regime switching may be dependent on underlying economic fundamentals. Recent research has witnessed a synthesis of comovement and nonlinearity features of cycles since there is room for the analysis by incorporating both factor structure and regime switching (see Diebold and Rudebusch (1996) Chauvet (1998, 2001) and Kim and Nelson (1998) among others).

The harmonization of two different methods of business cycle analysis also gave rise to Markov-switching vector autoregression (MS-VAR) models developed by Krolzig (1997). This framework constitutes the multivariate generalization of the Hamilton's single equation model. In these extended models there is an unobserved state driven by an ergodic Markov process that is common to all series. In a sequence of papers, Krolzig has studied the statistical analysis of the Markov Switching vector autoregressive (MS-VAR) models and their application

[1] Studies on modeling comovements include the dynamic factor models of Sargent and Sims (1977), Geweke (1977) and Stock and Watson (1993). It was stated that comovement may be due to dependence on a common factor.

[2] State-dependent dynamic behavior is also characterized by Threshold Autoregression (TAR) models of Tong (1990) and Hansen (1997) where regimes are determined by the past values of the time series itself.

to dynamic multivariate systems (Krolzig (1998, 2000, 2001), Krolzig *et al* (2002)). In subsequent studies, Clements and Krolzig (2002, 2003) discussed the characterization and the testing of business cycle asymmetries based on MS-VAR models. Pelagatti (2002) estimated a duration dependent MS-VAR model by using a multimove Gibbs sampler since the computational burden in using the ML approach to such models is high. Ehrmann *et al.* (2003) combined both Markov-switching and structural identifying restrictions in a VAR model to analyze the reaction of variables to fundamental disturbances.

Despite these very influential recent developments both in theoretical and empirical literature, the analysis of Turkish business cycles has been somewhat limited and concentrated heavily on the leading indicators approach. Some empirical contributions in this context were made by Üçer *et al* (1998), and Kibritçioğlu *et al* (1998) (See also Alper (1998, 2002), Aruoba (2001) and Uygur (2000)). In another recent paper, Ertuğrul and Selçuk (2001) attempted to explain the formation of boom-bust cycles after 1989 by taking a descriptive approach. However, none of these studies explicitly analyzed the stochastic properties of business cycles in a rigorous econometric framework.

Our major aim in this paper is to contribute in empirical modeling of Turkish business cycles with the help of MS models. Of our particular concern are MS-VAR models where the unobserved state is assumed to be common to all series used in model specifications. We consider both the comovement and the nonlinearity of the cyclical process of Turkish economy by employing a variety of MS-VAR models in which some or all of the parameters are allowed to change with the regime. Even though our concern is on the determination of business cycle turning points, a comparative forecasting experiment was also conducted. We have two major findings. First, by using likelihood ratio tests we found strong evidence in favor of the nonlinear MS models. Second and more importantly, MS-VAR models with various macro aggregates and changing variance parameters appeared to be the most successful specifications with superior forecast performance. The paper is organized as follows. Section 2 describes the various specifications of MS-VAR model and the estimation process via EM algorithm. Section 3 gives a brief overview of the pertinent events of Turkish economy in the considered period. Section 4 introduces the data set and presents the empirical results obtained from the application of various MS-VAR models to univariate and multivariate time series. The final section concludes.

2. MARKOV-SWITCHING VECTOR AUTOREGRESSIONS (MS -VAR)

We will first review the MS-VAR class of models and then continue with the estimation process via the EM algorithm.

2.1 The Model

MS-VAR class of models provide a convenient framework to analyze multivariate representations with changes in regime. They admit various dynamic structures, depending on the value of the state variable, s_t, which controls the switching mechanism between various states. In these models, some or all of the parameters may become varying with regard to the regime prevailing at time *t*. Besides, business cycles are treated as common regime shifts in the stochastic processes of macroeconomic time series. In other words, both nonlinear and common factor structures of the cyclical processes are represented at the same time.

Consider the MS-VAR process in its most general form:

$$y_t = v(s_t) + A_1(s_t)\, y_{t-1} + \ldots + A_p(s_t)\, y_{t-p} + \varepsilon_t \tag{1}$$

where $y_t = (y_{1t},\ldots,y_{nt})$ is an n dimensional time series vector, v is the vector of intercepts, $A_1,\ldots,A_p$ are the matrices containing the autoregressive parameters and ε_t is a white noise vector process such that $\varepsilon_t \mid s_t \sim NID\left(0, \Sigma\left(s_t\right)\right)$. The MS-VAR setting also allows for a variety of specifications. Krolzig (1997) established a common notation to provide simplicity in expressing the models in which various parameters are subject to shifts with the varying state. Table 1 gives an overview of the MS-VAR models.

[Table 1 is about here]

In Equation 1 the intercept term is assumed to vary with state beside other parameters. Intercept switch specification is used in cases where the transition to the mean of the other state is assumed to follow a smooth path. An alternative representation is obtained by allowing the mean to vary with the state. This specification is useful in cases where a one-time jump is assumed in the mean after a change in regime.[3]

In his seminal paper, Hamilton (1989) used a univariate two-state mean switch model of order four:

$$y_t - \mu_{s_t} = \phi_1(y_{t-1} - \mu_{s_{t-1}}) + \phi_2(y_{t-2} - \mu_{s_{t-2}}) + \phi_3(y_{t-3} - \mu_{s_{t-3}}) + \phi_4(y_{t-4} - \mu_{s_{t-4}}) + \varepsilon_t \qquad (2)$$

where $\varepsilon_t \sim N(0, \Sigma)$ and $s_t = 1,2$

Note that this is just a special form of Equation 1 where only the mean parameter denoted by μ is subject to change between regimes. With regard to the classification of Krolzig (1997), this is an MSM(2)-AR(4) model.

The description of the dynamics is complete after defining a probability rule of how the behavior of y_t changes from one regime to another. Markov chain is the simplest time series model for a discrete-valued random variable such as the unobserved state variable s_t. In all MS-VAR specifications it is assumed that the unobserved state s_t follows a first-order Markov-

[3] Note that the intercept v controls the mean of y_t through the relationship $\mu\left(s_t\right) = v\left(s_t\right)\left\{I - A_1\left(s_t\right) - \cdots - A_p\left(s_t\right)\right\}^{-1}$.

process. The implication is that the current regime s_t depends only on the regime one period ago, s_{t-1}

$$P\{s_t = j | s_{t-1} = i,\ s_{t-2} = k, \ldots\} = P\{s_t = j | s_{t-1} = i\} = p_{ij} \qquad (3)$$

where p_{ij} gives the probability that state i will be followed by state j.

These transition probabilities can be collected in a $(N \, x \, N)$ transition matrix, denoted as P. Each element in the transition matrix p_{ij} represents the probability that event i will be followed by event j.

$$P = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{N1} \\ p_{12} & p_{22} & \cdots & p_{N2} \\ \vdots & \vdots & \cdots & \vdots \\ p_{1N} & p_{2N} & \cdots & p_{NN} \end{bmatrix}$$

$$\text{with} \quad \sum_{j=1}^{N} p_{ij} = 1 \quad \text{where} \quad i = 1,2,\ldots,N \quad \text{and} \quad 0 \leq p_{ij} \leq 1 \qquad (4)$$

For a two-state case, we can represent the transition probabilities by a (2×1) vector, $\hat{\xi}_{t|t}$, whose first element is $P\left(s_t = 1 | \psi_t\right)$ where $\psi_t = \{\psi_{t-1}, y_t\}$ and ψ_{t-1} contains past values of y_t. If we know the value $\hat{\xi}_{t-1|t-1}$, then it would be straightforward to form a forecast of the regime for t given the information at t-1 and collect the terms for the probabilities of s_t = 1,2 in a vector denoted by $\hat{\xi}_{t|t-1}$ as follows:

$$\hat{\xi}_{t|t-1} = \begin{bmatrix} P\left(s_t = 1 \middle| \psi_{t-1}\right) \\ P\left(s_t = 2 \middle| \psi_{t-1}\right) \end{bmatrix} \tag{5}$$

We can specify the probability law of the observed variable y_t conditional on s_t and ψ_{t-1} and collect them in a (2×1) vector η_t:

$$\eta_t = \begin{bmatrix} f(y_t|s_t = 1, \psi_{t-1}) \\ f(y_t|s_t = 2, \psi_{t-1}) \end{bmatrix} \tag{6}$$

The joint probability of y_t and s_t is then given by the product

$$f\left(y_t, s_t = j \middle| \psi_{t-1}\right) = f\left(y_t \middle| s_t = j, \psi_{t-1}\right) P\left(s_t = j \middle| \psi_{t-1}\right), \quad j = 1,2 \tag{7}$$

The conditional density of the tth observation is the sum of these terms over all values of s_t. For a two-state case:

$$f\left(y_t \middle| \psi_{t-1}\right) = \sum_{s_t=1}^{2} \sum_{s_{t-1}=1}^{2} f\left(y_t \middle| s_t, \psi_{t-1}\right) P\left(s_t \middle| \psi_{t-1}\right) = \eta' \hat{\xi}_{t/t-1} \tag{8}$$

Then, the output $\hat{\xi}_{t|t}$ can be obtained from the input $\hat{\xi}_{t-1|t-1}$ by following the steps described in Hamilton (1994, Chapter 22).

2.2 Estimation

Hamilton’s (1989) classical algorithm consists of two parts. In the first part, population parameters including the joint probability density of unobserved states are estimated and in the second part, probabilistic inferences about the unobserved states are made by using a nonlinear filter and smoother. Filtered probabilities $P(s_t = j|\psi_t)$ are inferences about s_t conditional on information up to time t and smoothed probabilities $P(s_t = j|\psi_T)$ are inferences about s_t by using all the information available in the sample where $t = 1,2,\ldots T$.

The conventional procedure for estimating the model parameters is to maximize the log-likelihood function and then use these parameters to obtain the filtered and smoothed inferences for the unobserved state variable s_t. However this method becomes disadvantageous as the number of parameters to be estimated increases. Generally in such cases, the Expectation Maximization (EM) algorithm, originally described by Dempster *et al.* (1977) is used. This technique starts with the initial estimates of the hidden data and iteratively produces a new joint distribution that increases the probability of observed data. These two steps are referred to as expectation and maximization steps. The EM algorithm has many desirable properties as stated in Hamilton (1990).[4]

3. A BRIEF ACCOUNT of the TURKISH ECONOMY and BUSINESS CYCLES

Over the last two decades, Turkish economy has attained high growth rates in spite of high inflation. However, growth path was erratic since the economy also recorded significant negative growth interrupting the expansionary periods. A brief look at the striking events of Turkish economy during 1987-2002 clearly displays that macroeconomic instability is the hallmark of this period. There are five serious drops in aggregate economic activity of Turkish economy for the last fifteen years.[5] The first one took place in 1988 as a result of the disinflation program in February. After the adoption of convertible exchange rates in 1989, Turkey attracted foreign

[4] See Dempster *et al.* (1977) for a detailed description of the EM algorithm and Krolzig (1997) for its application to MS-VAR Models.
[5] In figure 1 most of these recessions and ensuing expansions can be seen.

short-term capital due to high interest rates which led the economy to become addicted to short term capital movements. However, large current account deficits and increasing demand for foreign reserves set a limit to the capital inflows resulting in an escalation in the volatility of domestic money markets. As a result, Turkish economy was negatively affected by the Gulf War in 1991 which led to large withdrawals of domestic and foreign deposits from the banking system. The openness of the economy associated with fiscal imbalances also complicated the macroeconomic management. High inflation and capital inflows led to an appreciation of the real exchange rate during the 1990-1993 period. In late 1993, Treasury started to cancel most of the auctions and Central Bank expanded credit to the public sector. This turbulent environment led to a run from TL resulting in a devaluation and sudden loss of reserves accompanied by record levels for overnight interest rates. On the 5^{th} of April 1994, the government declared a new stabilization package. From the beginning of 1996 until the Russian crisis in July 1998, the economy attained high rates of growth due to large capital inflows. Starting with the second half of 1998, the growth rate of output turned out to be negative due to increasing interest rates and worldwide recession. The recession was deepened by two earthquake disasters. Year 2000 started with a new disinflation program. Optimistic expectations of market participants led to an abrupt decline in interest rates. At the beginning of November, banking sector is forced to a rapid transition with new regulations. This led to a discomfort in financial markets and more liquidity demand arose in order to close short positions. The natural consequence was a noteworthy increase in interest rates. The belief that the authorities were no longer able to defend the exchange rate led to the abandonment of the parity on February 21, 2001.

As is evident, the instability of the GNP growth has been the main indicator of the cyclical pattern of the Turkish economy. This points out to the need for rigorious empirical modeling of the Turkish business cycles. Next section presents the results obtained from the application of a variety of MS-VAR specifications to capture the cyclical dynamics of the Turkish Economy during the period under consideration.

4. EMPIRICAL RESULTS

In this section we will present the results of the econometric specifications used for modeling the Turkish business cycles between 1988 and 2002. We will begin by introducing the data set and the results from the model selection procedure. Then, we will interpret the findings and compare the predictive performances of the alternative models.

4.1. Data Analysis

In the empirical analysis, four aggregate series namely, the real Gross National Product (RGNP), Composite Leading Indicator (CLI), Total Manufacturing Industry Production Index (TMI), and Aggregate Consumption (CS) are used. These variables are graphed in Figure 1. We focus on the period in which the economy is linked with the external markets since most quarterly data are available from mid-1980s.[6] It is crucial to note that the series that are frequently used in business cycle analysis like employment, wages and aggregate hours worked are not available in quarterly frequency for the considered sample period.[7]

One other variable included in various specifications is the CLI, which is considered to be a useful business cycle predictor.[8] The ability of the CLI to forecast future growth of GNP is

[6] The data set is obtained from the electronic data distribution system of the Central Bank of Turkey.
[7] Diebold and Rudebush (1996), Kim and Nelson (1998) and Chauvet (2001) are some examples which benefit from different series of labor market data.
[8] CLI is a new index constructed by the Central Bank which includes series of Production Amount of Electricity, Discounted Treasury Auctions Interest Rate Weighted by the Amount Sold, Import of Intermediate Goods and the CBRT Business Tendency Survey on selected topics.

examined in a number of studies (see Granger *et al.* (1993), Hamilton and Perez-Quiros (1996), Camacho and Perez-Quiros (2002), Huh (2002), and Emerson and Hendry (1996)).

RGNP and TMI are seasonally adjusted using a multiplicative moving average method. In order to achieve stationarity, one hundred times natural logarithms of the first differences of the series are used.

[Figure 1 is about here]

Some descriptive statistics including the mean growth rate, the standard deviation of growth, the coefficient of variation and the distribution of quarters are presented in Table 2. The visual evidence points out to little difference in average growth rates of RGNP, CLI, TMI and CS. The standard deviations of all the series are very close whereas the coefficient of variation shows that relative dispersion is much higher for CLI than the other ones.

[Table 2 is about here]

It may be interesting to note that the mean and standard deviation of recessionary and expansionary periods do show similar patterns across macro variables. In other words, by looking at the descriptive statistics, one can discern a dual structure between positive and negative growth periods. In what follows, we review model specification tests.

4.2 Choosing the appropriate MS specifications for the Turkish Business Cycles[9]

Our model selection process consists of two steps. In the first step, for choosing among different MS specifications, Akaike Information (AI), Hannah-Quinn (HQ) and Schwarz (SC) criteria are used. The alternative specifications were, MS models with mean, intercept and variance coefficients that are allowed to switch across regimes. Then, all models are tested for linearity by taking the linear model as the null hypothesis and the regime-switching model as the alternative. We applied these selection criteria both for univariate and multivariate MS Models. Only two

[9] All computations were performed using Gauss and the MS-VAR package of Ox. Detailed information regarding MS-VAR modeling in Ox can be found in Krolzig (1997, 1998).

states are assumed where state 1 is a low growth state indicating the recessions whereas state 2 is a high growth state associated with expansions.[10] The transition between states is characterized by a first order Markov chain and duration independency is also assumed.

For univariate model selection, a mean switch model (MSM(2)-AR(4)), an intercept switch model with changing variance (MSIH(2)-AR(4)) and a benchmark linear AR(4) model are estimated using RGNP for the period from 1988:Q2 through 2001:Q4.[11] Table 3 reports the specification test results of these alternative models. As is obvious from the table, the performance of all three MS models are better than that of the nested linear AR(4) model. Hamilton's classic MSM(2)-AR(4) specification appeared to be statistically most satisfactory on the basis of AIC, HQ and SC. This shows that it is an appropriate starting point for the analysis of Turkish business cycles.

[Table 3 is about here]

One of the main advantages of the MS-VAR framework is that through these specifications, comovements among various macro aggregates can be better handled. The bivariate model we adopt is the heteroskedastic intercept switch model (MSIH(2)-VAR(2)) including RGNP and CLI.[12] For a multivariate specification we have estimated the same model using all the series under consideration namely RGNP, CLI, TMI and CS. The comparison of these models with the nested linear VAR(2) model is illustrated in Table 4. It is apparent that both MS-VAR specifications performed better than their linear counterparts.

[Table 4 is about here]

In order to test between linearity versus non-linear regime switching specifications a testing procedure developed by Ang and Bekaert (2001) is used. In this paper it is suggested that

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[10] Less parsimonious three state models were also tried but no improvement in model performance took place.
[11] These models are selected since they are robust to other univariate specifications like MSI-AR and MSMH-AR.
[12] We also tried various MSMH-VAR and MSI-VAR specifications and higher order MSIH-VAR models but all were outperformed by the MSIH(2)-VAR(2) specification with respect to criteria considered.

the underlying distribution can be approximated by a $\chi^2(q)$ distribution where q represents the number of restrictions and nuisance parameters that are not defined under the null hypothesis.[13] Table 5 presents the results of this testing procedure. LR statistics show that all four models confidently reject the null of linearity with significance levels indicated in brackets. The LR statistics for all models support the presence of regime shifts.

[Table 5 is about here]

All of the above presented estimation statistics and the results of linearity tests highlight the need for nonlinear models to characterize cyclical dynamics. In the light of this finding, we will proceed with the estimation results of the MS models and their implications for the cyclical structure of Turkish economy.

4.3 Comments on Estimated MS Models

Table 6 reports the maximum likelihood estimates of MS models obtained by the EM algorithm. For the MSM(2)-AR(4) model, μ_1 refers to the average growth rate of quarterly RGNP series in state 1 whereas μ_2 is the average growth rate of RGNP in state 2. For all other models the intercept, v, instead of the mean is assumed to be state dependent.

[Table 6 is about here]

For Hamilton's (1989) univariate mean switch model, the estimated quarterly growth rate is 1.8 % in expansions and -6.1 % in recessions. This result points out to the volatility of output growth during periods of recessions and expansions. AR coefficients are negative implying a negative serial correlation in the growth rate of RGNP. Transition probabilities of regimes are 0.41 for regime 1 and 0.92 for regime 2. The implication is that a recession is generally not

[13] Hansen (1992) developed another testing procedure where the supremum of the calculated standardized LR statistics is utilized.

followed by another recession but this is not true for expansions. Expected durations of both regimes that are calculated from these transition probabilities are 1.68 quarters for recessions and 11.96 quarters for expansions. This is another finding which points out to the asymmetric nature of Turkish real GNP over the different phases of the business cycle.

The second column of Table 6 shows the results for MSIH-AR specification where the intercept and the variance are assumed to be state-dependent. Since the intercept term controls the mean of the dependent variable, we can say that the model differentiates the two trends in RGNP for two different states. Regime dependent variance points out to higher volatility during recessions. The variances separating two regimes are 11.09 for recessions and 3.24 for expansions. The model estimates longer recessions with an average duration of 3.68 quarters. When we relax the assumption of constant variance, we see that the model captures the persistency in recessions. The implication is that volatility break is one of the defining characteristics of Turkish RGNP.

For the bivariate MS-VAR model, we define RGNP and CLI as dependent variables and set the lag order to 2. States are differentiated not only by their average growth rates but also by their variances. Both of the series are more volatile in the recessionary periods. The CLI seems to be much more variable than RGNP when the economy is experiencing a recession. One important difference between the univariate and the bivariate specifications is that the MSIH(2)-VAR(2) model captures more temporal persistency for recessions than the univariate specifications. The transition probability of recessions is 0.79 which implies an expected duration of 4.78 quarters.

In the multivariate version of MS-VAR model, all series namely RGNP, CLI, TMI and CS are used. Two lags of GNP and one lag of CLI are included with reference to AI, SC and HQ criteria. Lags of TMI and CS are excluded since otherwise the results deteriorate quite significantly. As is obvious from Table 6, intercepts of equations for all four variables support the presence of two regimes. For all series except TMI, volatility is higher in recessions with CLI having the highest variance. Transition probabilities point out to an expected duration of 3.58 quarters for recessions and 7.58 quarters for expansions. Expected durations of recessions are lower and expansions are higher than the bivariate model.

Optimal inferences of turning points are obtained from the smoothed probabilities of the Markov states. Due to the decision rule proposed by Hamilton (1989), if $P(s_t = 1|\psi_T) > 0.5$, the economy is in a recession, otherwise it is in an expansion. Figure 2 gives a graphical display of the filtered and smoothed probabilities of regime 1 produced by all four models. Smoothed probabilities of all models display that downswings are abrupt and much shorter while upswings are more gradual and highly persistent. Among the five RGNP drops in the last 15 years, most severe ones are the last three of them. These are also the periods of more persistent economic contractions. For all the estimated MS models, regimes are differentiated by the average growth, persistence and volatility. This is an important superiority of nonlinear regime switching models over linear alternatives since the latter cannot distinguish between subperiods having different characteristics.

[Figure 2 is about here]

As is obvious from Figure 2, MSM-AR model depicts very precisely the recessions of 1991, 1994, 1999 and 2001 associated with serious drops in GNP whereas it is unable to detect a recession in 1988. Unlike MSM-AR, smoothed probabilities of MSIH-AR indicate the short recession in 1988 as well.

Panels c and d of Figure 2 show the smoothed probabilities of bivariate and multivariate MS models respectively. One important difference between these models is that the first one determines two recessions in 1999 and 2001 while the latter determines the whole period as a single long recession. When we include TMI and CS to this MS-VAR specification, both the filtered and smoothed probabilities determine a recovery period in year 2000 which is missed by the bivariate model.

Therefore, although the univariate MS models fare well in capturing most recessionary turning points, MS-VAR models have been more successful in capturing the duration of recessions. A final comparison between models will be made based on forecast performance.

4.4 Which model to choose?

To make a more formal assessment of the comparative ability of the alternative models to predict the future GNP changes, we conducted a forecasting experiment which relies on one-step ahead prediction errors, i.e., the forecast error at time t is defined as $y_t - E[y_t|\psi_{t-1}]$ which means that inferences about the unobserved state are based on only past values of y_t.

The forecasting performance of the models are compared on the basis of the mean absolute error (MAE), root mean squared error (RMSE) and Theil inequality coefficient (TIC). Table 7 summarizes the comparison results. As is obvious from the table, extending the analysis to a multivariate setting improves forecast performance. The MSIH-VAR model utilizing all four series outperforms the others.

[Table 7 is about here]

To sum up we have the following ranking among various MS specifications. First, both the univariate and multivariate MS specifications are preferred to their linear counterparts. Among the univariate MS specifications, mean and variance switch models appeared to be more satisfactory than that of other conventional specifications. The MS-VAR models with changing variance turned out to better reflect the Turkish business cycle characteristics and produce superior predictive performance during the period observed in this paper. All these results imply that the regime inference of the multivariate MSIH-VAR model is based on a reliable characterization of cyclical dynamics.[14]

Figure 3 plots the actual and fitted values besides one-step predictions for each variable determined by the MSIH-VAR model. Visual inspection also shows that the fit of the model is satisfactory except for the periods of excessive volatility in aggregate output.

[Figure 3 is about here]

Table 8 reports the dating of the turning points of Turkish business cycles determined by the smoothed probabilities of the MSIH-VAR model. Peaks refer to the beginning of recessions where troughs refer to their end.

[Table 8 is about here]

The model captures all five recessionary periods of the sample. The first slowdown of the sample period started in the third quarter of 1988 as a result of a disinflation package and lasted for two quarters. Smoothed probabilities determine the following peak at the third quarter of 1990. The contraction due to the Gulf War persists for the following two quarters. Starting from the end of 1993, the economy enters into another low growth phase as a result of subsequent policy mistakes. Cancellation of domestic public debt auctions and the domestic credit expansion of the Central Bank led to a severe recession that lasted for four quarters.

The smoothed probabilities determine the proceeding peak at the second quarter of 1998, just before the Russian crisis. As a result of large capital outflows and high interest rates, the economy enters into a recession that lasts for five quarters. The recession deepened as a result of two earthquakes and the increased taxes afterwards. A new disinflation program that proposed a pre-announced crawling peg system and structural reforms regarding the banking sector was introduced at the beginning of 2000. However another deep recession took place due to the

[14] MSIH-VAR models also supports the presence of regime shifts stronger than the MSMH-VAR model. This implies that transitions between regimes are not one-time jumps. Instead the mean converges smoothly to its new level after a change in regime takes place.

failure of the new policies. Two subsequent crises took place in November 2000 and in February 2001. In the third quarter of 2000, the model determines the peak and signals the coming recession. The contraction starting from this point persists till the last quarter of 2001.

5. CONCLUSION

In this paper, we employed various specifications of MS-AR and MS-VAR models to empirically characterize the state dependent dynamics of the Turkish business cycles between 1988 and 2002. Our findings can be summarized as follows. Linearity of GNP series is severely rejected implying that there is regime switching structure in Turkish business cycles. Among the univariate models, changing variance specification seems to capture the persistency of recessions. This may imply that the Turkish economy has experienced structural breaks in the volatility of aggregate economic activity over the last 15 years. Further improvements are obtained as we switched to a multivariate setting. By including additional variables besides RGNP an improvement in model performance is observed with reference to one-step prediction errors. A reliable chronology of the turning points of business cycles is also formed. Direct tests of comovement and asymmetry across business cycles will constitute our future research program.

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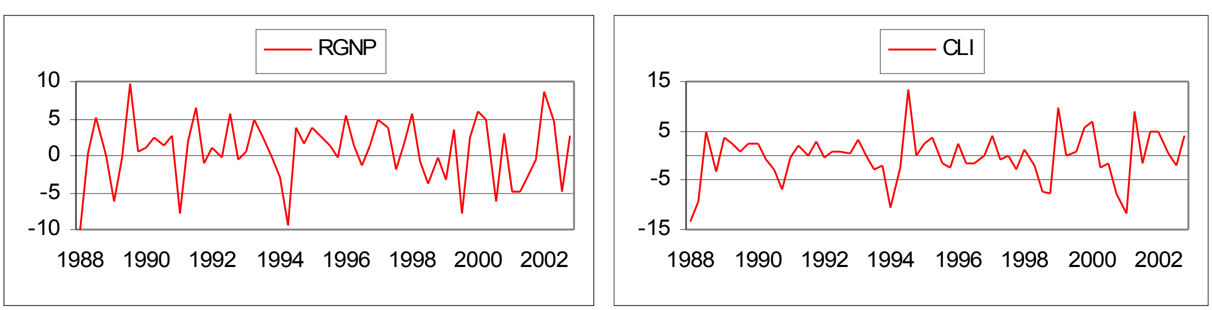
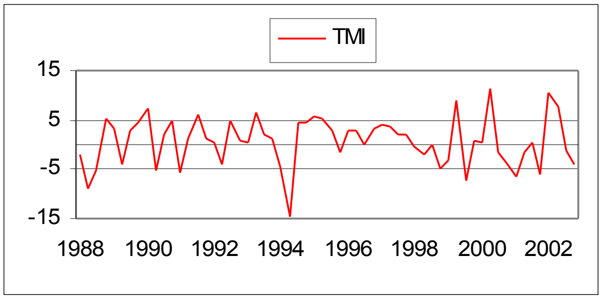
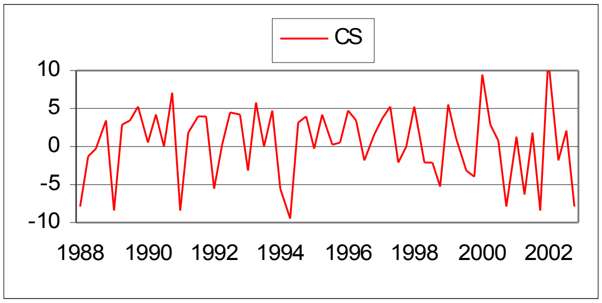
FIGURES:

Figure 1: The variables under analysis*



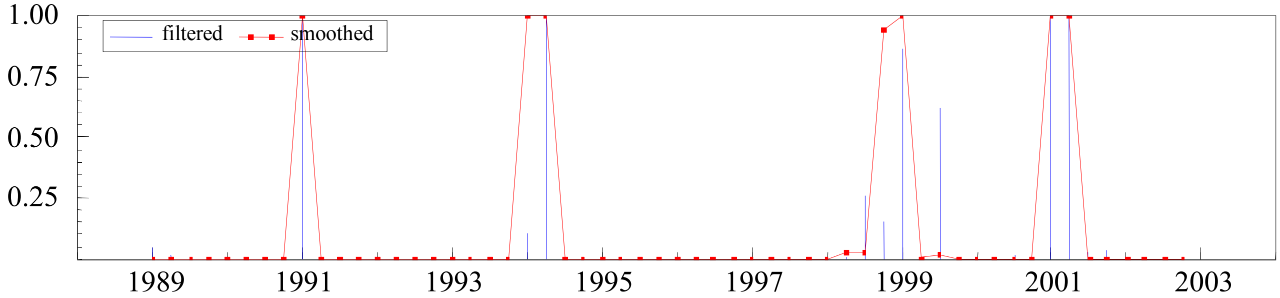




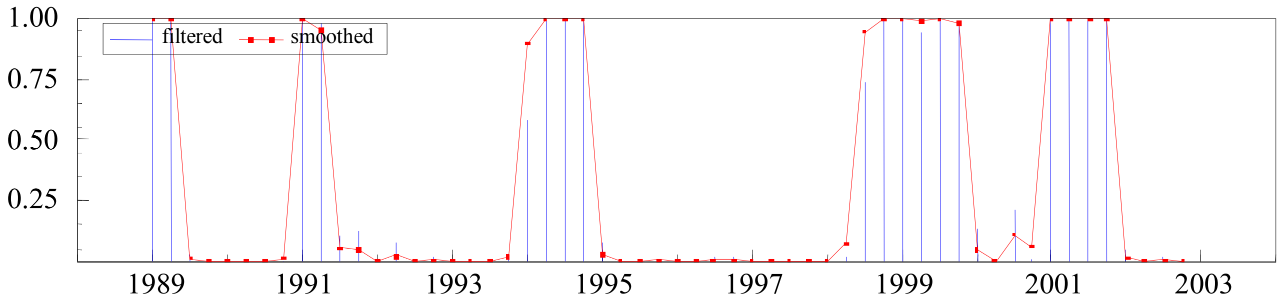
* Percentage changes in the variables calculated as hundred times log diffference.

Figure 2: Filtered and Smoothed Probabilities of Regime 1 for Various Models:

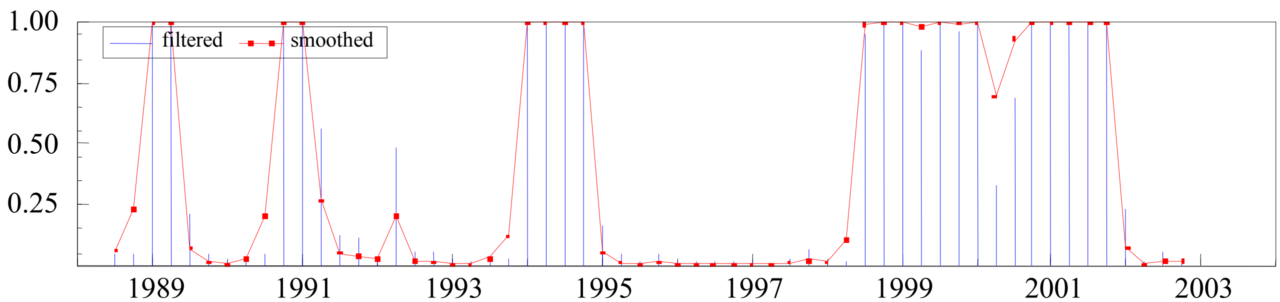
(a) MSM(2)-AR(4) Model of RGNP



(b) MSIH(2)-AR(4) Model of RGNP



(c) MSIH(2)-VAR(2) Model of RGNP and CLI



(d) MSIH(2)-VAR(2) Model of RGNP,CLI,TMI and CS

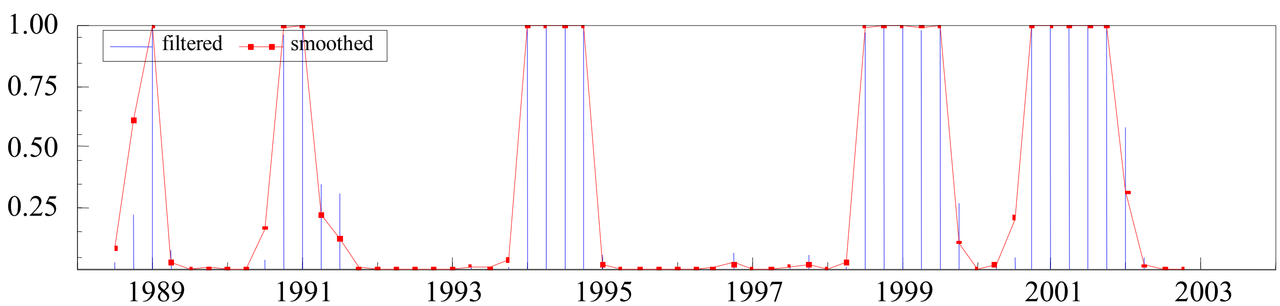
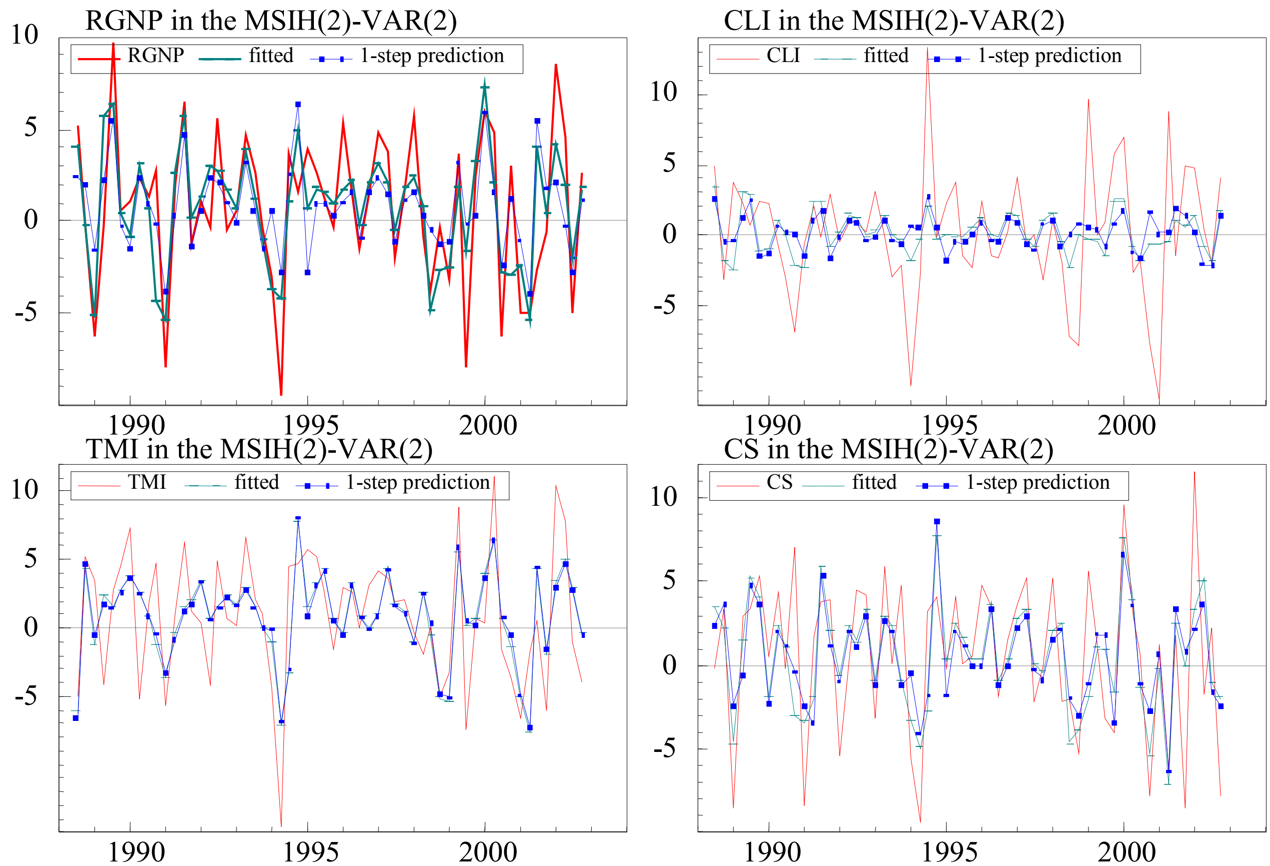


Figure 3: Fit of the MSIH(2)-VAR(2) Model for RGNP,CLI, TMI and CS



TABLES:

Table 1: Types of MS-VAR Models

Notation	μ	v	Σ	A_i
MSM(M)-VAR(p)	varying	-	invariant	invariant
MSMH(M)-VAR(p)	varying	-	varying	invariant
MSI(M)-VAR(p)	-	varying	invariant	invariant
MSIH(M)-VAR(p)	-	varying	varying	invariant
MSIAH(M)-VAR(p)	-	varying	varying	varying

μ : mean, v : intercept Σ : variance A_i : matrix of autoregressive parameters

Table 2: Descriptive Statistics of Series: 1988Q1 to 2002Q4

	RGNP	TMI	CLI	CS
Mean	0.60%	0.65%	-0.16%	0.43%
St.Dev.	4.28%	4.91%	4.90%	4.77%
CV	7.11	7.53	-30.20	11.18
Mean (+)	3.42%	3.81%	3.34%	3.57%
Mean (-)	-3.34%	-4.08%	-3.66%	-4.29%
St.Dev.(+)	2.41%	2.89%	2.76%	2.61%
St.Dev.(-)	2.62%	2.87%	3.19%	2.90%
N (-)	35	36	30	24
N (+)	25	24	30	36
N (Total)	60	60	60	60

Mean , St. Dev. and CV (coefficient of variation) give the values for the whole sample period. Mean (+) and (-) refers to the mean growth rates of positive and negative quarters and St.Dev (+) and (-) refers to the standard deviations of them respectively. N(-) is the number of quarters which have negative growth rates and N(+) is number of quarters which have positive growth rate.

Table 3: Diagnostic statistics of various MS specifications for RGNP and the linear benchmark

	MSM(2)-AR(4)	MSIH(2)-AR(4)	Linear AR(4)
Log L	-142.721	-145.363	-156.196
No. of parameters	9	10	6
AIC criterion	5.4186	5.5487	5.7927
HQ criterion	5.5448	5.6889	5.8769
SC criterion	5.7441	5.9104	6.0097

Table 4: Diagnostic Statistics of multivariate MS specifications and their linear benchmarks

	MSIH(2)-VAR(2) with RGNP and CLI	Linear VAR(2)	MSIH(2)-VAR(2) with RGNP,CLI,TMI and CS	Linear VAR (2)
Log L	-301.166	-319.739	-587.731	-613.321
No. of parameters	20	13	42	26
AIC criterion	11.0747	11.4737	21.7148	22.0455
HQ criterion	11.3515	11.6536	22.2960	22.4053
SC criterion	11.7852	11.9356	23.2069	22.9692

Table 5: Wald Specification Tests

Models	Test Statistic	RGNP	RGNP, CLI	RGNP, CLI, TMI, CS

MSM-AR	$\chi^2(3)$	26.95[0.0000]		
MSIH-AR	$\chi^2(4)$	21.67[0.0002]		
MSIH-VAR	$\chi^2(7)$		37.14[0.0000]	
MSIH-VAR	$\chi^2(16)$			51.18[0.0000]

Table 6: Maximum Likelihood Estimates of Various MS-VAR Specifications

Parameter	**MSM-AR**	**MSIH-AR**	**MSIH-VAR for RGNP and CLI**		**MSIH-VAR for RGNP, CLI, TMI and CS**			
	RGNP	*RGNP*	*RGNP*	*CLI*	*RGNP*	*CLI*	*TMI*	*CS*
μ_1	-6.33							
μ_2	1.88							
v_1		-3.88	-1.56	-0.51	-2.03	-1.25	0.04	-1.33
v_2		4.76	3.61	1.12	2.93	1.47	0.98	1.76
RGNP_1	-0.66	-0.60	-0.44	-0.21	-0.28	-0.27	0.21	0.21
RGNP_2	-0.76	-0.62	-0.56	-0.14	-0.44	-0.23	-0.46	-0.46
RGNP_3	-0.55	-0.31						
RGNP_4	-0.03	-0.04						
CLI_1			0.35	-0.06	0.63	-0.01	0.63	0.30
CLI_2			0.13	0.01				
Σ_1	4.80	11.09	16.26	37.05	14.82	39.82	19.67	22.77
Σ_2		3.24	2.87	4.68	4.66	5.06	10.02	8.78
p_{11}	0.41	0.73	0.79		0.72			
p_{22}	0.92	0.88	0.86		0.87			
Exp.duration of recessions	1.68	3.68	4.78		3.58			
Exp.duration of recessions	11.96	8.60	7.34		7.58			

Table 7: Model Comparison Based on One-Step Prediction Errors

	MSM(2)-AR(4)	MSIH(2)-AR(4)	MSIH(2)-VAR(2) with RGNP and CLI	MSIH(2)-VAR(2) with RGNP, CLI, TMI and CS
MAE	2.8070	3.0369	2.5487	2.4474
RMSE	3.8396	3.9236	3.3808	3.1668
TIC	0.5628	0.6363	0.4926	0.4839

MAE: Mean Absolute Error, RMSE: Root Mean Squared Error, TIC: Theil Inequality Coefficient

Table 8: Dating of the Turkish Business Cycle Turning Points Using Smoothed Probabilities of MSIH-VAR Model: 1988Q3 – 2002Q4

Peak	Trough	Duration*
1988*Q*3	1989:*Q*1	2
1990*Q*3	1991*Q*1	2
1993*Q*4	1994*Q*4	4
1998*Q*2	1999*Q*3	5
2000*Q*3	2001*Q*4	5

* Duration denotes the length of a recession in quarters.