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Modeling Business Cycle Fluctuations through Markov Switching VAR: An Application to Iran

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Abstract

IN this paper, the Iranian Business Cycle characteristics were investigated via 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 Iranian real GDP between 1988:Q2 - 2008:Q3. The empirical analysis consists of mainly three parts. First, two kinds of alternative specifications were tried and we were adopted best specification with respect to various diagnostic statistics. Then, selected models were tested against their linear benchmarks. LR test results imply 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 detect the three recessionary periods experienced by the Iranian economy between 1988:Q2 and 2008:Q3. Finally, based on inference from this model a chronology of business cycle turning points was determined.

JEL Codes: E32, C32.
Key Words: Markov Switching Models, Business Cycles, MSVAR, Iran.

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, co-movement 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 mod-

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els 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 co-movement 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 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 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 multi-move Gibbs sampler since the computational burden in using the MLE approach to such models is high.

Despite these very influential recent developments both in theoretical and empirical literature, the analysis of Iranian business cycles has been somewhat limited and concentrated heavily on the leading indicators approach (see Moradi (2001), Dargahi (2003), Ghafari (2008)). 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 Iranian 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 co-movement and the nonlinearity of the cyclical process of Iranian economy by employing MS-VAR models. 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 Iranian economy in the con-

[1] Studies on modeling co-movements include the dynamic factor models of Sargent and Sims (1977), Geweke (1977) and Stock and Watson (1993). It was stated that co-movement 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.

sidered period. Section 4 introduces the data set and presents the empirical results obtained from the application of MS-VAR models to univariate and multivariate time series. The final section is results.

2 Mrkov-Switching Vector AutoRegression(MS-VAR)

We will first review the MS-VAR class of models and then continue with the estimation process via the EM algorithm. By allowing for changes in regime of the process generating the time series, the MS-VAR model has been proposed as an alternative to the constant-parameter, linear time-series models of the earlier Box and Jenkins (1970) modelling tradition. The general idea behind this class of regime-switching models is that the parameters of a, say, K-dimensional vector time series process $\{y_t\}$ depend upon an unobservable regime variable $s_t \in \{1, ..., M\}$, which represents the probability of being in a particular state of the world.

$$p(y_t|Y_{t-1}, X_t, s_t) = \begin{cases} f(y_t|Y_{t-1}, X_t; \theta_t), & \text{if } s_t = 1 \\ \quad \vdots \\ f(y_t|Y_{t-1}, X_t; \theta_M), & \text{if } s_t = M. \end{cases} \tag{1}$$

where $Y_t = \{y_{t-j}\}_{j=0}^{\infty}$ denotes the history of y_t and X_t are strongly exogenous variables; θ_m is the parameter vector associated with regime m.
MS-VAR class of models provides a suitable 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 regiems. 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:

$$y_t = \upsilon(s_t) + A_1(s_t)y_{t-1} + \cdots + A_p(s_t)y_{t-p} + \epsilon_t \tag{2}$$

Where $y_t = (y_{1t}, y_{2t}, \cdots, y_{nt})$ is an n dimensional time series vector, $\upsilon(s_t)$ is the vector of intercepts or parameter shift functions, for example:

$$\upsilon(s_t) = \begin{cases} \upsilon_1, & \text{if } s_t = 1 \\ \vdots \\ \upsilon_M, & \text{if } s_t = M. \end{cases} \tag{3}$$

$A_1, A_2, \cdots, A_p$ 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 MS-VAR model provides a very flexible framework for modeling time series subject to regime shifts. While all parameters of the conditional model can be made dependent on the state s_t of the Markov chain, in practice, only some parameters of interest

will be regime dependent while the others will be regime invariant. In order to establish a unique notation for each model, we specify with the general MS(M)term the regime-dependent parameters:

M	markov switching **M**ean,
I	markov switching **I**ntercept,
A	markov switching **A**utoregressive parameters,
H	markov switching **H**eteroscedasticity.

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.
In Equation 1 the intercept term is assumed to vary with state beside other parameters.

Table 1: Types of MS-VAR Models

Notation	μ	υ	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

Note :

μ= Mean, υ= Intercept Terms
Σ= Variance, A_i= matrix of autoregressive 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:

$$\begin{aligned}(y_t - \mu_{st}) = \phi_t(y_{t-1} - \mu_{st-1}) + \phi_2(y_{t-2} - \mu_{st-2}) + \\ \phi_3(y_{t-3} - \mu_{st-3}) + \phi_4(y_{t-4} - \mu_{st-4}) + \varepsilon_t\end{aligned} \tag{4}$$

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

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

time series model for a discrete-valued random variable such as the unobserved state variable s_{t-1}. In all MS-VAR specifications it is assumed that the unobserved state st follows a first-order Markov-process. The implication is that the current regime st depends only on the regime one period ago, s_{t-1}.

$$P\{s_t = j | s_{t-1} = i, s_{t-2} = k, \cdots\} = P\{s_t = j | s_{t-1} = i\} = p_{ij} \tag{5}$$

Where p_{ij} gives the probability that state i will be followed by state j.
These transition probabilities can be indicated in a $(N \times N)$ 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.

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

With $\sum_{j=1}^{N} p_{ij} = 1$, where $i = 1, 2, \cdots, N$ and $0 \leq p_{ih} \leq 1$. (6)

For a two-state case, we can represent the transition probabilities by a (2×1) vector, $\hat{\xi}_{t|t}$, whose first element is $p(s_t = 1|\psi_t)$ 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:

$$\hat{\xi}_{t|t-1} = \begin{bmatrix} p(s_{t=1}|\psi_{t-1} \\ p(s_{t=2}|\psi_{t-1} \end{bmatrix} \tag{7}$$

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:

$$\eta_t = \begin{bmatrix} f(y_t|s_{t=1}, \psi_{t-1} \\ f(y_t|s_{t=2}, \psi_{t-1} \end{bmatrix} \tag{8}$$

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

$$\begin{aligned} f(y_t, s_t = j|\psi_{t-1}) &= \\ &f(y_t|s_t = j, \psi_{t-1})P(s_t = j|\psi_{t-1}), \qquad j = 1, 2 \end{aligned} \tag{9}$$

The conditional density of the t^{th} observation is the sum of these terms over all values of s_t. For a two-state case:

$$f(y_t|\psi_{t-1}) = \sum_{s_t=1}^{2} \sum_{s_{t-1}=1}^{2} f(y_t|s_t, \psi_{t-1})P(s_t|\psi_{t-1}) = \acute{\eta}\hat{\xi}_{t|t-1} \tag{10}$$

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).

3 Estimation

Hamilton's (1989) classical algorithm consists of two steps. In the first step, population parameters including the joint probability density of unobserved states are estimated and in the second step, 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 $t = 1, 2, \cdots, T$.

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].

4 A Brief on the Iranian Economy and Business Cycles

Over the last two decades, Iranian economy has attained erratic growth rates. However, the economy also recorded significant negative growth interrupting the expansionary periods. A brief look at the striking events of Iranian economy during 1988-2008 clearly displays that macroeconomic instability is the hallmark of this period. There are three serious drops in aggregate economic activity of Iranian economy for the last twenty years. The first one took place in 1992 as a result of the adjustment price program. High inflation led to an appreciation of the real exchange rate during the 1991-1995 periods.

As is evident, the instability of the GDP growth has been the main indicator of the cyclical pattern of the Iranian economy. This points out to the need for rigorous empirical modeling of the Iranian 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 Iranian Economy during the period under consideration.

5 Empirical Results

In this section we will present the results of the econometric specifications used for modeling the Iranian business cycles between 1988: Q2 and 2008: Q3. 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] See Dempster et al. (1977) for a detailed description of the EM algorithm and Krolzig (1997) for its application to MS-VAR Models.

5.1 Data Analysis

In the empirical analysis, three growth rate of aggregate series namely, the Real Gross Domestic Product (GDP), Industrial Production Index (IP), and Aggregate Consumption (CS) in growth rate form are used. These variables are graphed in Figure 1. 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.[5] GDP and IP are seasonally adjusted. In order to achieve stationarity, one hundred times natural logarithms of the first differences of the series are used.

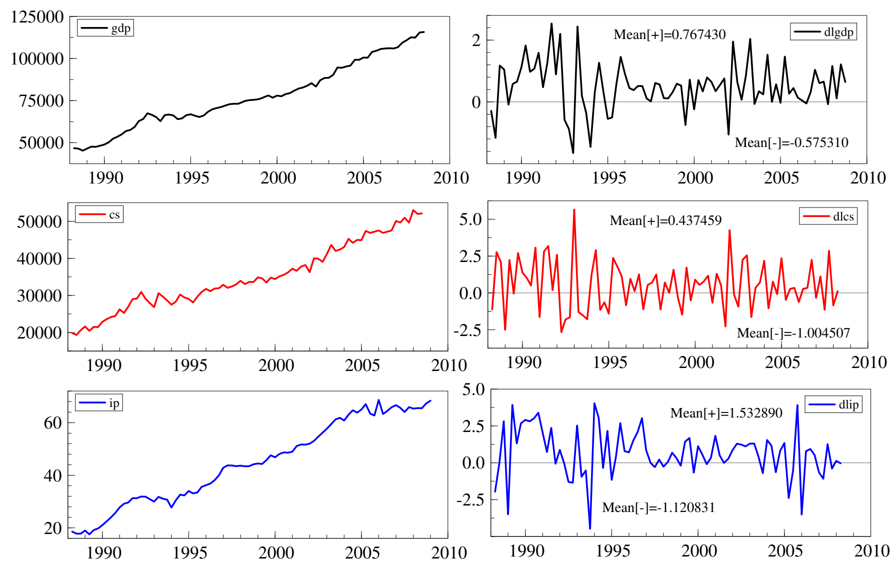

Figure 1: The Level and growth rate of variables under analysis

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 GDP, IP 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 $DLCS$ than the other ones. 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.

[5]Diebold and Rudebush (1996), Kim and Nelson (1998) and Chauvet (2001) are some examples which benefit from different series of labor market data.

Table 2: Descriptive Statistics of variables under analysis

	DLGDP	DLIP	DLCS
Mean	0.485621	0.674279	0.5172683
Std. Deviation	0.801851	1.634270	1.646525
CV	1.651181	2.423729	3.183159
Mean (+)	0.767430	0.437459	1.532890
Mean (-)	-0.575310	-1.004507	-1.120831
Std. Deviation (+)	0.604448	1.089142	1.179491
Std. Deviation (-)	0.512491	1.187352	0.682058
Number (-)	17	27	31
Number (+)	64	54	50
Number (Total)	81	81	81

Note :

Sample of data is for time period 1988Q2 to 2008Q3. Mean, St. Deviation 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 Std. Deviation (+) and (-) refers to the standard deviations of them respectively. Number(-) is the number of quarters which have negative growth rates and Number(+) is number of quarters which have positive growth rate.

6 Choosing the Appropriate MS Specifications:

Our model selection process consists of two steps. In the first step, for choosing among different MS specifications, Akaike Information (AIC), Hannan-Quinn (HQ) and Schwarz Bayesian criteria (SBC) are used. The alternative specifications were MS models with mean, intercept 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 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. 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 GDP for the period from 1988:Q2 through 2008:Q3. 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 SBC. This shows that it is an appropriate starting point for the analysis of Iranian business cycles.

One of the main advantages of the MS-VAR framework is that through these specifications, co-movements among various macro aggregates can be better handled. The univariate model we adopt is the mean switch model (MS(2)-AR(2)) including GDP. For a multivariate specification we have estimated the same model using all the series

Table 3: Diagnostic statistics of various MS-VAR & Linear Models

	MSM(3)-VAR(2)	MSIH(3)-VAR(2)	MSIA(3)-VAR(2)	MSIAH(3)-VAR(2)
Log L	-256.7902	-160.7518	-138.4325	-130.9841
No. P.	39	51	75	87
Obs-in Sys	237	237	237	237
AIC	7.4884	5.3608	5.4034	5.5186
HQ	7.9570	5.9736	6.3045	6.5640
SBC	8.6581	5.8904	7.6528	8.1280
	MSMH(2)-VAR(2)	MSH(3)-VAR(2)	MSI(3)-VAR(2)	Linear VAR(2)
Log L	-254.5507	-159.5277	-177.7514	-195.7020
No. P.	51	45	39	27
Obs-in Sys	237	237	237	237
AIC	7.3755	5.1779	5.4874	5.6380
HQ	8.3483	5.7186	5.9560	5.9625
SBC	9.2651	6.5276	6.6571	6.4478

Note :

Log L = Log Likelihood
No.P.= Number of Parameters
Obs-in Sys = Number of Observations in the System
AIC = Akaike Information Criterion
HQ = Hannan-Quinn Information Criterion
SBC = Shawarz Bayesian Information Criterion

under consideration namely GDP, IP 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: Diagnostic statistics of various MS & Linear Models for GDP

	MSIH(3)-VAR(2)	Linear VAR(2)	MS(3)-AR(2)	Linear AR(2)
Log L	-160.7518	-195.7020	-116.9155	-147.8685
No.P.	51	27	11	3
Obs-in Sys	237	237	80	80
AIC	5.3608	5.6380	3.1979	3.7717
HQ	5.9736	5.9625	3.3292	3.8075
SBC	6.8904	6.4478	3.5254	3.8610

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 the underlying distribution can be approximated by a distribution where q represents the number of restrictions and nuisance parameters that are not defined under the null hypothesis. 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: Diagnostic statistics of various MS & Linear Models for GDP

Models	Test Statistic	LR - Stat.	P-Value
MSM(3)-VAR(2)	$\chi^2(6)$	122.1763	[0.0000]
MSIH(3)-VAR(2)	$\chi^2(18)$	69.9005	[0.0000]
MSIA(3)-VAR(2)	$\chi^2(42)$	114.5391	[0.0000]
MSIAH(3)-VAR(2)	$\chi^2(54)$	129.4324	[0.0000]
MSMH(2)-VAR(2)	$\chi^2(18)$	117.6975	[0.0000]
MSH(3)-VAR(2)	$\chi^2(12)$	72.3485	[0.0000]
MSI(3)-VAR(2)	$\chi^2(6)$	35.9012	[0.0000]

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 Iranian economy.

7 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, refers to the average growth rate of quarterly GDP series in state 1 whereas is the average growth rate of GDP in state 2. For all other models the intercept, , instead of the mean is assumed to be state dependent.

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 GDP. 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 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 Iranian real GDP over the different phases of the business cycle.

The second column of Table 6 shows the results for MSI-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 GDP 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

Table 6: Maximum Likelihood Estimates of MSIH(3)-VAR(2) Specifications

Parameter	MSIH(3)-VAR(2) Specifications								
	DLGDP			DLIP			DLCS		
	Coef.	S-Er.	T-Stat.	Coef.	S-Er.	T-Stat.	Coef.	S-Er.	T-Stat.
υ_1	0.0079	0.036	0.22	-1.2885	0.542	-2.37	-1.2579	0.206	-6.09
υ_2	0.0051	0.014	0.35	0.7822	0.176	4.44	0.9809	0.176	5.56
υ_3	-0.0194	0.026	-0.73	2.8858	0.289	9.95	2.3331	0.389	5.98
$DLGDP_{t-1}$	-0.4674	0.027	-17.0	0.2709	0.342	0.79	-0.4647	0.298	-1.56
$DLGDP_{t-2}$	0.4778	0.017	28.18	-0.2218	0.224	-0.98	-0.2706	0.143	-1.88
$DLIP_{t-1}$	0.0004	0.006	0.07	-0.0005	0.085	-0.01	0.3087	0.068	4.52
$DLIP_{t-2}$	0.0037	0.006	0.58	-0.0457	0.084	-0.54	-0.0695	0.052	-1.33
$DLCS_{t-1}$	0.4860	0.007	66.95	-0.1121	0.093	-1.20	-0.4164	0.065	-6.34
$DLCS_{t-2}$	0.4684	0.015	31.52	-0.3091	0.182	-1.69	-0.0650	0.162	-0.40
	S.E of Regimes								
	DLGDP			DLIP			DLCS		
Σ_1	0.109710			1.702220			0.557514		
Σ_2	0.076993			0.952224			1.088063		
Σ_3	0.090055			0.949554			1.499280		
	Matrix of Transition Probabilities								
	P_{i1}			P_{i2}			P_{i3}		
P_{1j}	0.3482			0.1750			0.4768		
P_{2j}	0.0000			0.9794			0.0206		
P_{3j}	0.3977			0.0000			0.6023		
	Regime 1			Regime 2			Regime 3		
Duration*	1.53			48.46			2.51		

Note :

Regime 1 = Recession State.
Regime 2 = Expansion State (with Low growth rate).
Regime 3 = Expansion State (with High growth rate).

is that volatility break is one of the defining characteristics of Iranian GDP.

For the bivariate MS-VAR model, we define GDP and CS 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 GDP when the economy is experiencing a recession.*** One important difference between the univariate and the bivariate specifications is that the MSI(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 GDP, IP and CS are used. Two lags of GDP and one lag of CLI???? are included with reference to AIC, SBC and HQ criteria. Lags of IP 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 IP, 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 GDP drops in the last twenty 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 sub periods having different characteristics.

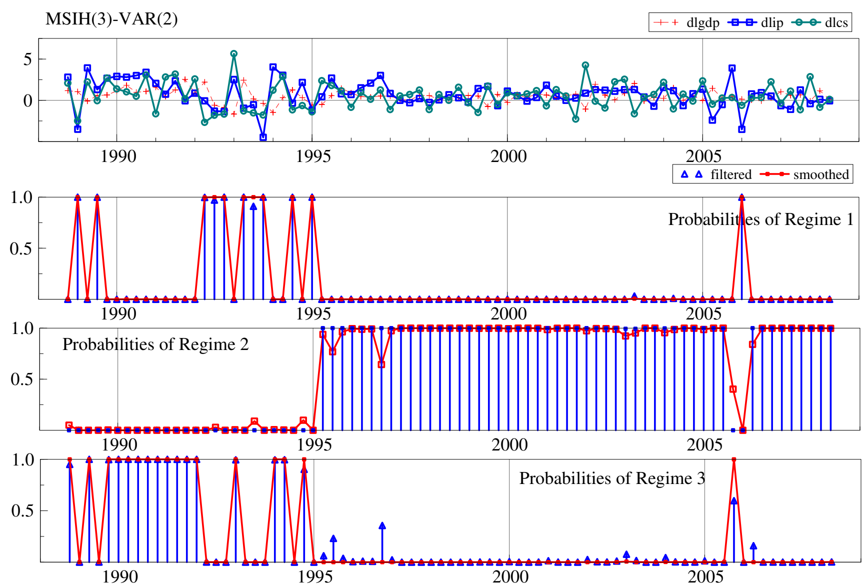

Figure 2: The variables under analysis

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 GDP 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 IP 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.

8 Which model to choose?

To make a more formal assessment of the comparative ability of the alternative models to predict the future GDP 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 MSI-VAR model utilizing all four series outperforms the others.

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

	MSIH(3)-VAR(2)	Linear VAR(2)	MS(3)-AR(2)	Linear AR(2)
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

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

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 Iranian 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 MSI-VAR model is based on a reliable characterization of cyclical dynamics.

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

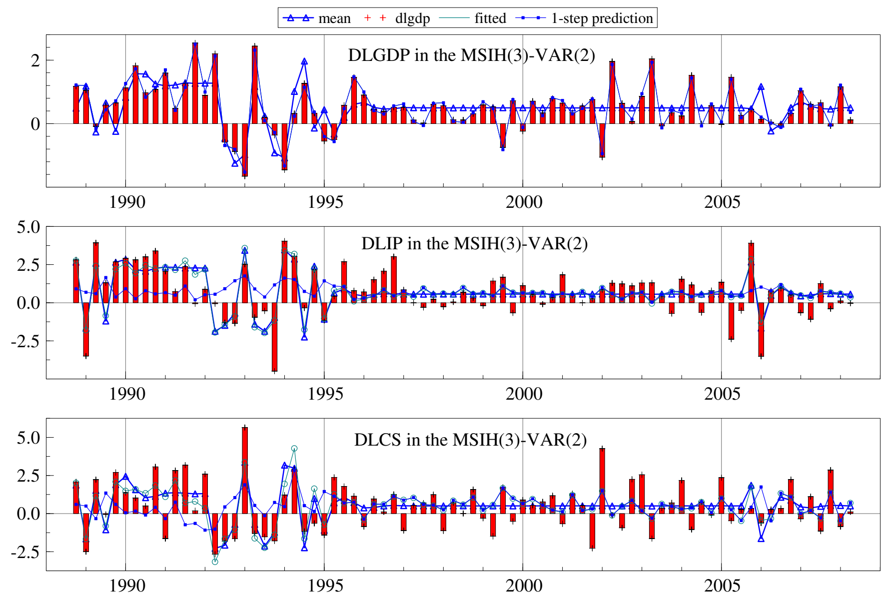

Figure 3: The variables under analysis

Table 8 reports the dating of the turning points of Iranian 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: : Dating of Turning Points Using Probabilities of MSIH(3)-VAR(2) Model

Peaks of Business cycle	Troughs of Business cycle	Duration *	Probablity
1989:Q1	1989:Q1	1	1.0000
1989:Q3	1989:Q3	1	0.9987
1992:Q2	1992:Q4	2	0.9995
1993:Q2	1993:Q4	2	0.9999
1994:Q3	1994:Q3	1	0.9999
1995:Q1	1995:Q1	1	0.9995
2006:Q1	2006:Q1	1	1.0000

∗ Duration is length of a recession in quarters.

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

Table 9: : Regime properties of the MSIH(3)-VAR(2) Model.

	Transition probabilities			Observations	Erg.Prob	Duration
Recession	0.3482	0.1750	0.4768	11.0	0.0899	1.53
Expansion	0.0000	0.9794	0.0206	51.0	0.7627	48.46
High growth	0.3977	0.0000	0.6023	17.0	0.1474	2.51

Table 10: : Regime properties of the MS(3)-AR(2) Model.

	Transition probabilities			Observations	Erg.Prob	Duration
Recession	0.4976	0.1707	0.3317	6.0	0.0686	1.99
Expansion	0.0179	0.9252	0.0568	57.6	0.7480	13.38
High growth	0.1148	0.2410	0.6442	16.4	0.1834	2.81

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. Cancelation 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 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.

9 Results

In this paper, we employed various specifications of MS-AR and MS-VAR models to empirically characterize the state dependent dynamics of the Iranian business cycles between 1988:Q2 and 2008: Q3. Our findings can be summarized as follows. Linearity of GDP series is severely rejected implying that there is regime switching structure in Iranian business cycles. Among the univariate models, changing variance specification seems to capture the persistency of recessions. This may imply that the Iranian economy has experienced structural breaks in the volatility of aggregate economic activity over the last 20 years. Further improvements are obtained as we switched to a multivariate setting. By including additional variables besides GDP 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 co-movement and asymmetry across business cycles will constitute our future research program.

References

[1] Ang, A and G. Bekaert, (2001). *" Stock Return Predictability: Is it There?"* NBER Working Papers 8207, National Bureau of Economic Research, Inc.

[2] Burns, A. F., W.C. Mitchell (1946), *"Measuring business cycles"*, New York: NBER.

[3] Camacho, M., Perez-Quiros, G., (2002), *" This is what the leading indicators lead"*, Journal of Applied Econometrics 117, 61-80.

[4] Chauvet, M. (2001), *"A monthly indicator of Brazilian GDP"*, The Brazilian Review of Econometrics Vol. 21, No. 1, (Revista de Econometrcia).

[5] Clements, M.P., Krolzig, H.-M. (2002). *" Can oil shocks explain asymmetries in the US business cycle? "*, Empirical Economics 27, 185-204. Reprinted as pages 91-112 of: Hamilton, J.D. and B. Raj (Eds) (2002) 'Advances in Markov-switching models', Heidelberg: Physica.

[6] Clements, M.P., Krolzig, H.-M. (2003), *cycle asymmetries: characterization and testing based on Markov-switching Autoregression* , Journal of Business and Economic Statistics, 21, 196 - 211.

[7] Dempster, A.P., N.M. Laird & D.B. Rubin (1977), *"Maximum likelihood from incomplete data via the EM algorithm"*, Journal of the Royal Statistical Society, B39, 1-38.

[8] Diebold, F. X., G.D. Rudebusch (1996), *"Measuring business cycles: A modern perspective"*, The Review of Economics and Statistics 78 (1), 67-77.

[9] Diebold, F.X., J.H. Lee, G.C. Weinbach (1994), *"Regime switching with time-varying transition probabilities"* in: C. Hargreaves (ed.), Nonstationary Time Series Analysis and Cointegration, Oxford: Oxford University Press, 283-302.

[10] Ehrmann, M., Ellison, M., Valla, N., (2003), *" Regime dependent impulse response functions in a vector Markov-switching model"* , Bank of Finland-Discussion Papers 11/2001.

[11] Emerson, A., Hendry, D., (1996), *" an evaluation of forecasting using leading indicators"* Journal of Forecasting 15, 271-291.

[12] Enders, W, (2004), *"Applied Econometric Time Series"*, 2nd Edition, New York, John Wiley.

[13] Filardo, A. J. (1994), *"Business cycle phases and their transitional dynamics"*, Journal of Business and Economic Statistics 12, 299-308.

[14] Geweke, J. (1977), *"The dynamic factor analysis of economic time-series models"*, in: D. J. Aigner and A.S. Goldberger (Eds.), Latent Variables in Socioeconomic Models, Amsterdam: North Holland,365-383.

[15] Granger, C., T. Terasvirta, H. Anderson (1993), *"Modeling nonlinearity over the business cycle"*, in: J.H. Stock and M.W. Watson (eds.) Business Cycles, Indicators and Forecasting, Chicago: University of Chicago Press for NBER, 311-325.

[16] Hamilton, J. D. (1989), *"new approach to the economic analysis of nonstationary time series and the business cycle"*, Econometrica 57, 357-384.

[17] Hamilton, J. D. (1990), *"Analysis of time series subject to changes in regimes"*, Journal of Econometrics 45, 39-70.

[18] Hamilton, J., Perez-Quiros, G. (1996), *"what do the leading indicators lead?"*, Journal of Business 69, 27-49.

[19] Hansen, B. E. (1992), *"the likelihood ratio test under non-standard conditions: Testing the Markov trend model of GDP"* Journal of Applied Econometrics 7, 61-82.

[20] Hansen, B. E. (1997), *"Inference in TAR Models"* Studies in Nonlinear Dynamics and Econometrics 2, (1), 1-14.

[21] Harvey A. C. and A .Jaeger,(1993), *" Deterendng, stylized facts and the business cycles"* , Journal of Applied Econometrics, Vol,8.

[22] Hodrick, R. J and E. C. Prescott (1980), *" Postwar US Business Cycles: An Empirical Investigation"* , Carnegie- Mellon University, Department of Economics, Discussion Paper No. 451.

[23] Huh, H.S. (2002), *" GDP growth and the composite leading index: a nonlinear causality analysis for eleven countries"* , Economics Letters 77, 93-99.

[24] Kim, C.J., C. R. Nelson (1998), *" Business cycle turning points, A new coincident index and tests of duration dependence based on a dynamic factor model with regime switching"* , Review of Economics and Statistics, 80, 188-201.

[25] Krolzig, H.-M. (1998), *" modeling of Markov-switching vector Autoregression using MSVAR for Ox"* , Discussion Paper, Department of Economics, University of Oxford: http://www.economics.ox.ac.uk/hendry/krolzig.

[26] Krolzig, H.-M. (2000), *"Predicting Markov-switching vector autoregressive processes"*, Journal of Forecasting,

[27] Krolzig, H.-M., Marcellino, M., Mizon, G. (2002), *"A Markov-switching vector equilibrium correction model of the UK labor market"*, Empirical Economics, 27, 233-254. Reprinted as pages 41-60 of: Hamilton, J.D.and B.Raj (eds), (2002), Advances in Markov-Switching Model, Heidelberg: Physica.

[28] Moradi, A. (2011), *" Forecasting of Iranian business cycle through Duration Dependent of Markov Switching Autoregressive Models with Bayesian Approach"*, Unpublished Doctoral Dissertation Islamic Azad university - Science and Research Branch [In Persian].

[29] Pelagatti, M. (2002), *" Duration-dependent Markov-switching VAR models with applications to the business cycle analysis"*, Universita di Milano-Bicocca.

[30] Sargent, T. J., C. Sims (1977), *"Business cycle modeling without pretending to have too much a priori Theory"*, in: C. Sims (Ed), New Methods of Business Cycle Research, Minneapolis: Federal Reserve Bank of Minneapolis.

[31] Stock, J.H., M., W. Watson (1993), *" a procedure for predicting recessions with leading indicators: econometric issues and recent experience"*, in: J.H. Stock and M.W. Watson (eds.) Business Cycles, Indicators and Forecasting, Chicago: University of Chicago Press for NBER, 255-285.

[32] Tong, H. (1990), *Nonlinear Time Series Analysis: A Dynamical System Approach* , New York: Oxford University Press.