10. MODELING BUSINESS CYCLES IN THE ROMANIAN ECONOMY USING THE MARKOV SWITCHING APPROACH[1]

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Abstract

I use the Markov Switching AR approach to model the business cycles in Romanian economy for the 1991-2008 period using monthly data on industrial production. The time series used allows for a comparison with previous dating of Romanian business cycles. Generally, the MS-AR performs well, confirming the previous finding about turning points in business cycles during the transition period. At the same time, it suggests that the ongoing recession started earlier than conventionally thought and that it may last more than a year and a half.

Keywords: business cycles, Markov switching, nonlinear methods, transition economies, mathematical methods

JEL Classification: C22, C50, E32

1. Introduction

One of the market economy characteristics is the recurrence of business cycles. Long periods of expansion may induce the illusion that the business cycles are a phenomenon of the past. This happens from time to time (the boom period before the Great Depression or the long expansion before the current global recession), but the experience teaches us that the recessions are actually inevitable. The recessions are most likely necessary periods of restructuring and reform, when the boom misallocations are corrected.

The current recession was surprising not only through the fact that it was almost unexpected, but also through the fact that it appears severe and it has a global reach. Romania was affected due to the drop in exports, the fall in investments, and the

1 This research is part of the IDEI Program, Exploratory Research Projects ID_1046, „Nonlinear Models of Forecasting the Economic Development”, Institute for Economic Forecasting, Romanian Academy, 2008 competition, Year 1 - Term: 15 December 2009.

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tightening of credit. Romania, thus, ended a period of high growth that started in 2000, and passed from a high economic growth to a drop in the GDP. Such changes in dynamics are harder to model using the linear approach, requiring a more complex framework. One possibility to address the modeling of business cycles in such a context is the regime switching approach, which dates back to Hamilton (1989).

Previous analyses of business cycles in Romania treated the subject using the classical approach. Caraiani (2004) dated the business cycles in Romania, using the classical dating procedure on monthly industrial production. He also derived stylized facts of business cycles in Romania using the second order moments, like cross-correlations and standard deviations of the main monthly macroeconomic variables.

A few studies approached the business cycles phenomenon in Romania using a nonlinear approach, such as Albu (2001), or Purica and Caraiani (2009). The latter paper used a nonlinear differential equation and calibrated it in order to reproduce the dynamics of business cycles in Romania. The simulation was done on monthly data, using the monthly index of industrial production. Quite remarkably, this simple nonlinear model was capable to capture the duration and the turning points, as well as the tendency of business cycles to dampen.

In this paper, I use a Markov-Switching model which I estimate on monthly data on industrial production. I compare the findings to those from previous papers on Romania with respect to dating of turning points and duration of regimes. The following section details the model used in this paper. In the third section I estimate the model and analyze the predictions of the model with respect to the data and other findings in the literature. I draw some conclusions in the fourth section and assess some possible extensions of this paper.

2. The Markov Switching Approach

One of the fundamental models in time series is the autoregressive models, AR(p), where a variable y_t is modeled as depending on its own p lags. Although very simple in its structure, this model serves for building more complicated models that econometricians are using in the analysis of the time series: ARMA, VAR, cointegration analysis, etc. However, all these techniques have in common the underlying hypothesis that the studied time series is a stationary linear process.

Apart from the classical analysis of time series, during the last decades, a new trend in applying nonlinear time series emerged. The contributions of Hamilton (1989), Hamilton (1990), Granger and Hallman (1991), Terasvirta (1994) and others, helped us to use a distinct and complementary approach to the classical framework. Models like regime-switching or threshold autoregressive allow for nonlinearities, by introducing the possibility of shifts in the time series process. This framework is particularly useful for the business cycle analysis, and it makes business cycle dating, the modeling of business cycles asymmetries, etc. possible.

The MS-AR approach is another extension of the AR() model to the nonlinear case. It assumes the existence of a finite number of states, each state being characterized by an AR() model. Hamilton (1989) suggested that the sudden changes in the dynamics of GDP can be modeled using a Markov switching process. The model switches between the different states following transition probabilities.

I use the following MS-AR model:

$$y_t = \alpha_{S_t} + \sum_{i=1}^{p} \beta_{i,S_t} y_{t-i} + \sigma_{S_t} \varepsilon_t \qquad (1)$$

where: S_t stands for the state at time t - there is a finite number of states;
p is the number of autoregressive elements;
α_{St} stands for the intercept coefficient, which varies with the states;
σ_{St} is the standard deviation, which differs along with the states;
$\beta_{i,St}$ shows the autoregressive coefficients for lags 1 to p for each state;
ε_t are the residuals characterized by a zero mean and a variance equal to 1.

The basic model presented here is characterized by constant transition probabilities. Recent research showed how to introduce time varying probabilities that improve the performance of these models – see, for instance, Durland and McCurdy (1994), who extended the standard framework to include duration-dependent transition probabilities.

As Hamilton (2008) argues, such a model is fit to reveal two features of macroeconomic data, very relevant for the business cycle analysis, namely a macroeconomic variable can exhibit a dramatic change in their dynamic (this may be due to a recession or an unexpected change in the macroeconomic policies), and most of the economic time series behave differently along the expansion and recessions phases.

3. Estimation of the MS-AR Model

I use data on the monthly industrial production, taken as a chained index series with the base in December 1990[2]. The series is seasonally adjusted and then the log-difference series is computed. This final series, which is stationary, is used in the econometric estimation.

There is a twofold argument in using the monthly industrial production index. One is that the series is available starting with 1990, while the quarterly GDP official series date back to 1998. Secondly, the use of the monthly index of industrial production allows for a comparison with previous studies on Romanian business cycles, like Caraiani (2004) or Purica and Caraiani (2009).

A two-state MS model was used, with one state for recession and one state indicating the expansion phase. The choice of the number of lags was a more difficult one. Since I used a monthly time series, I estimated 12 MS-AR models, with lags from 1 to 12. I compared the models based on their final maximum likelihood, as well as their predicted expected duration of regimes, see Table 1.

[2] *The data source is provided by the Monthly Statistical Bulletins of the National Institute of Statistics, Bucharest, Romania.*

Table 1

Comparing alternative MS-AR Models

Models MS-AR	Number of states	Number of lags	Expected duration regime 1	Expected duration regime 2	Log-Likelihood
1	2	1	48.7	16.9	407.14
2	2	2	59.3	18.5	413.44
3	2	3	57.6	15.6	413.24
4	2	4	57.7	15.6	412.58
5	2	5	51.9	15.5	411.69
6	2	6	63.9	16.0	412.67
7	2	7	54.5	15.7	413.37
8	2	8	42.8	15.4	417.07
9	2	9	57.2	14.5	418.82
10	2	10	28.7	5.84	429.03
11	2	11	22.5	2.17	438.35
12	2	12	7.55	2.90	417.04

Source: Author's own computations.

We see that adding one more lag, from model 1 to model 2, improves the Log-Likelihood considerable. At the same time, the models with 2 to 7 lags have almost the same Log-Likelihood, with a slight superiority for the MS-AR(2) model. Although adding more than 9 lags considerable improves the model, (except for the model with 12 lags), we see that the MS-AR(10) and MS-AR(11) lead to very improbable expected duration for regime 2 (recession phase). In the light of Romania's experience in business cycles, we can thus dismiss the last three models. We can also dismiss the MS-AR(8) model that predicts a much lower expected duration for the expansion phase (42 periods). We can finally choose between model 2, with 2 lags, and model 9, with 9 lags for the AR. But, based on the parsimony principle, and also looking at the statistical significance of the lags, we can choose the MS-AR(2) as our final model.

The final model used was a two-state MS-AR(2), as in equation 1. It was estimated using the maximum likelihood approach. The process indicated that the convergence was achieved. Based on the estimation, filtered and smoothed probabilities for the two states were derived. In Table 2, I present the results of the estimation. We can see that the AR() coefficients are significant, with the exception of the AR(1) coefficient for state 2. The transition probabilities are also presented in Table 2. The mean estimate for phase 2, namely α_2, shows a high negative value, implying that recessions in Romanian economy are severe, which is a fact confirmed by the data.

Figure 1 shows the smoothed probabilities for recessions and expansions in the Romanian economy. The smoothed probabilities suggest three periods of recession and two expansions. The high probabilities for the two phases may be due to the fact that during the expansions the growth was high, while the recession was severe (at least the initial adjustment in output at the beginning of the '90s, and the '97-'99 recession). We also notice the growth in the probability of a recession at the beginning of 2005 which, although it did not signal a recession, it signaled the adjustment in growth, following an electoral year, as the economic growth in 2004 was well above the economic potential.

Table 2

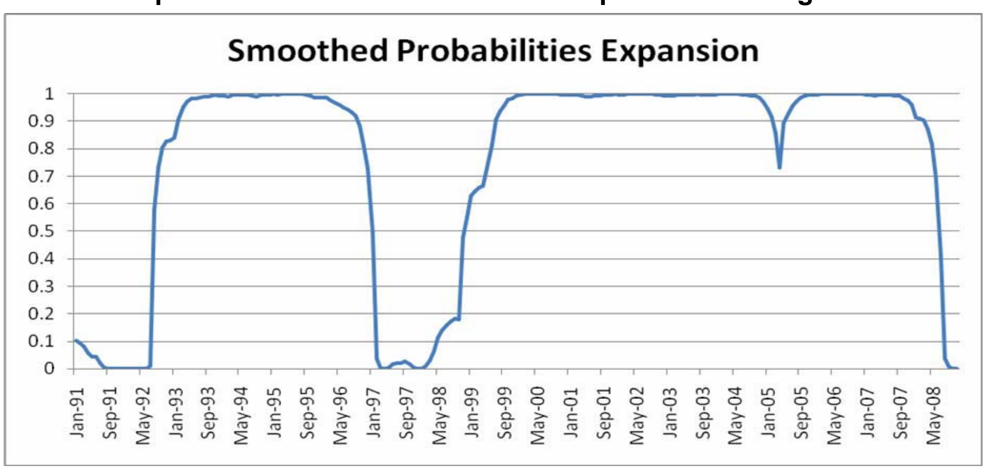
Maximum likelihood estimates for the MS(2)-AR(2) model

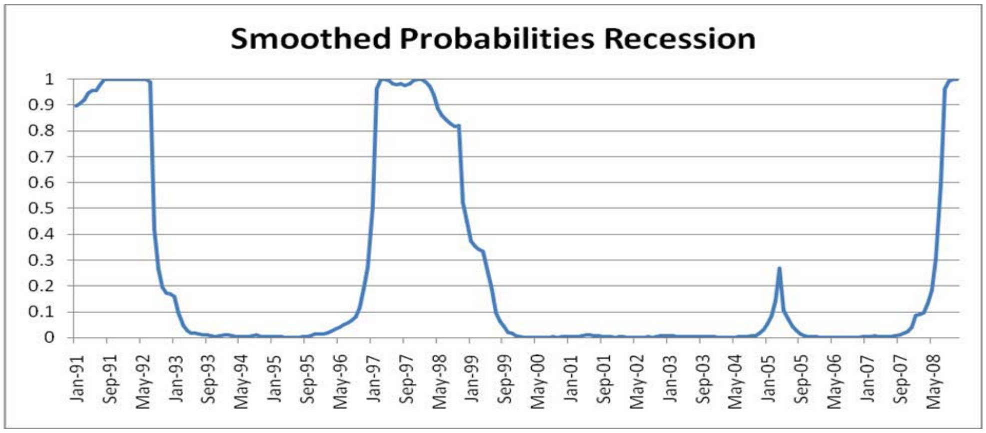
State parameters	Estimates	Probabilities parameters	Estimates
State 1		p_{11}	0.98
α_1	0.0099 (0.0024)	p_{12}	0.02
$\beta_{1,1}$	-0.55 (0.07)	p_{21}	0.05
$\beta_{1,2}$	-0.27 (0.07)	p_{22}	0.95
σ_1	0.028 (0.0016)		
State 2			
α_2	-0.0209 (0.0081)		
$\beta_{2,1}$	-0.08 (0.13)		
$\beta_{2,2}$	-0.26 (0.14)		
σ_2	0.054 (0.0057)		

Note: Standard errors in brackets.
Source: Author's own computations.

Figure 1

Smoothed probabilities of recessions and expansions during 1991-2008





Source: Author's own computations.

Based on the smoothed probabilities for recession and expansion, I derived the dating of Romanian business cycles (see Table 2). We can compare the findings here with those in Caraiani (2004) who applied the classical dating procedure on the industrial production index for the 1991-2004 period. Since the data starts in 1991, when the transformational recession specific to all transition economies was ongoing, the first peak is identified as of January 1991. The recession is estimated to end in September 1992, while Caraiani (2004) estimated that the recession ended in August 1992. The second recession starts in February 1997, according to the MS-AR(2) model which is close to Caraiani (2004), who predicted a turning point in December 1996. There is a slight difference with respect to the end of the second recession, as the MS-AR(2) model predicts that the minimum was reached in January 1999, while Caraiani (2004) predicted that the recession ended in July 1999. As for the ongoing recession, this model predicts an earlier starting date than conventionally thought, namely in August 2008. However, it should be pointed out that the industrial production may have a little bit different dynamics than the quarterly GDP which is the main measure of economic activity. At the same time, using the monthly production index can complete the information that is available through the quarterly GDP series.

Table 2

Dating business cycles in Romania using the MS-AR approach

Smoothed probabilities		Duration of recessions in months
Peak	Through	
January '91	September '92	21
February'97	January '99	24
August '08	-	-

Source: Author's own computations for the 1991-2008 period.

4. Conclusions

A Markov Switching model was estimated for the Romanian economy using data on the monthly production index between 1991 and 2008. The predictions of the model with respect to the turning points during the transition period are remarkably close to those in Caraiani (2004), who used the classical dating procedure. For the current cycle, the MS-AR(2) model predicts that the recession started earlier than we believed, in the 2008 fall, and given the expected duration of a recession of 18 months, the current recession may end in the first half of 2010.

The results here show that there is a great potential in using regime switching models for the analysis of macroeconomic dynamics in the Romanian economy. Future studies could take into consideration a three-state model that consider not only the recession and expansion phases, but also can distinguish between high growth and slow growth phases. Some other approaches could consider the character of a small open economy, by using variables like the exchange rate, debt, or the interest rate, in a multivariate MS model.

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