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Markov Switching Model for Financial Time Series

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Abstract

Modeling financial time series is an important step for its forecast and risk evaluation when financial assets are involved. In this context, this article presents a Markov Switching Model for BET series recorded during the period Oct-2000 - Sept-2014. It is shown that the model captures two phases in the series variation, even if the series is not stationary.

Key words: Markov Switching Model (MSwM), time series, BET
J.E.L. classification: C32, C58

1. Introduction

An important research area especially during the decades is represented by financial time series analysis, aiming at explaining the laws governing the series evolution in the context of a continuous change of financial markets. Stock markets are characterized by complex nonlinear dynamics that cannot be described by simple deterministic models. The stochastic component plays an essential role in determining their variability and evolution.

Finding a high-performance model of the process that generates financial series is essential for an accurate prediction of its future behavior, supporting the decisions for profitable trading strategies (Sinclair *et al,* 2008; Wagner *et al*, 2007).

Therefore, in this article, we propose a model for the evolution of the BET close monthly index for a period of 168 months that takes into account the stochastic component. This is a Markov Chain Monte Carlo (MSwM) that emphasizes the existence of two states in the series evolution and can be further used for forecasting the series behavior in the context of the continuous change of the capital market.

2. Theoretical background

The deterministic approach of data modeling is based on equations that completely describe the process evolution from which the data are taken, without the intervention of random factors. Unfortunately, the economic and financial systems cannot benefit from this approach since they can experience chaotic behavior due to dynamically generated internal and external noise (Chakraborti *et al*, 2007).

Before the publication of the research of (Mandelbrot, 1963) and (Fama, 1965), the financial data normality has been assumed as well as the markets' efficiency. Later, their studies on asset price series found some statistical properties of the asset prices random variations, common to different assets, markets, and different periods (Mandelbrot, 1982; Fama, 1998; Chakraborti *et al*, 2007).

Starting with the work of Fama (1965), different critiques of the financial market efficiency theory appeared, showing that the decisions taken by the players are not always rational and not all have access to the same information (Bărbulescu and Băutu, 2012; Degutis and Novickytė, 2014).

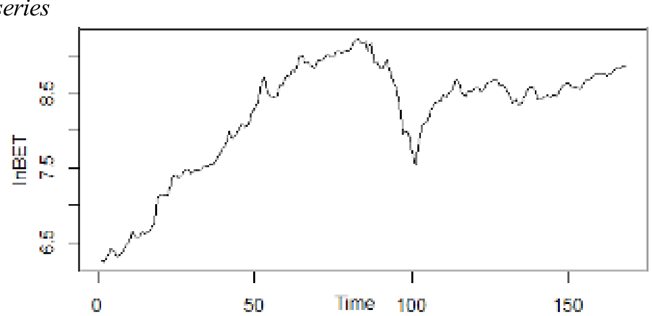
Therefore, the Adaptive Market Hypothesis, based on Darwin's evolution theory, has been proposed (Lo, 2004). It brings the evolving market idea into light, showing that the model followed by the market is evolutionary, based on competition, adaptation, and natural selection.

In this context, different approaches for modeling financial time series appeared, like artificial neural networks (Chen *et al*, 2006; Bărbulescu, 2018; Dragomir, 2017; Tache, 2009; Tache et al. 2010), gene expression programming (Cheng *et al*, 2018; Lee *et al*, 2014), support vector regression (Chen *et al*, 2006; Simian *et al*, 2020), hybrid (Bărbulescu and Băutu, 2012; Alhnaity and Abbod, 2020), all of them being based on the hypothesis of the financial series stochastic behavior. Therefore, we present an alternative model, MSwM, for financial time series, that captures the stochastic nature of the data.

3. Research methodology

The study series consists of BET monthly closed data, collected between Oct. 2000 and Sept. 2014. The logarithm of the data (Figure 1) has been taken to reduce the series variability, as recommended by the econometrics methodology. The new series is denoted by lnBET.

Figure no. 1. lnBET series



*Source:*Figure drawn by the authors after processing data from https://www.quandl.com/data/BUCHARESTSE/INDICES-Bucharest-Stock-Exchange-Indices

Statistical analyses have been performed for the lnBET series to determine its properties: the Shapiro - Wilk (normality test), the KPSS test (for stationarity in level and trend), and the Mann-Kendall test (for trend existence). The autocorrelation presence has been emphasized by the correlogram.

The tests have been performed at a 95% confidence level using the R software.

Secondly, we proposed the use of a Markov Switching Model (MSwM) of first-order for modeling the evolution of the study series.

The model takes the form:

$$X_t = \begin{cases} \alpha_1 + \varphi_1 X_{t-1} + a_{1t}, & \text{if } s_t = 1 \\ \alpha_2 + \varphi_2 X_{t-1} + a_{2t}, & \text{if } s_t = 2 \end{cases}, \tag{1}$$

where $a_{it} \sim \mathrm{IID}(0, \sigma_i^2)$, independent of each other, s_t is an unobservable state variable following a first-order Markov chain that has a matrix of the transition probabilities $(p_{ij})_{1 \le i,j \le 2}$, with:

$$p_{ij} = \mathrm{P}(s_t = j | s_{t-1} = i) \text{ and } p_{11} + p_{12} = p_{21} + p_{22} = 1. \tag{2}$$

A small transition probability p_{ij} shows that the system tends to stay longer in state *i*.

4. Findings

The Shapiro-Wilk test found enough evidence to reject the lnBET series normality (p-val = 3.924e-11). The Mann-Kendall trend test could not reject the hypothesis of a trend existence. The Sen slope found is 0.01114, and a corresponding p-value of 2.2e-16. The correlogram shows a high autocorrelation with an exponentially decreasing shape.

The results of the KPSS test do not support the trend stationarity and the level stationarity hypotheses since the p-values are smaller than 0.01. But, after taking the logarithm and the first-order difference, the stationarity hypothesis could not be rejected.

Therefore, a Markov Switching Model with two states has been built. The coefficients and the corresponding significance tests are presented in Table 1.

Table no. 1 Coefficients in MSwM

Regime 1			
Estimate	**Standard error**	**t-val**	**p-val**
0.1025	0.0537	1.9088	0.05629*
0.9901	0.0066	150.0152	<2E-16***
Residual standard error: 0.05589244			
Multiple R-squared :0.9953			
Regime 2			
Estimate	**Standard error**	**t-val**	**p-val**
0.8812	0.4597	1.9169	0.05525*
0.8832	0.0553	16.1519	<2E-16***
Residual standard error: 0.1458123			
Multiple R-squared:0.9322			

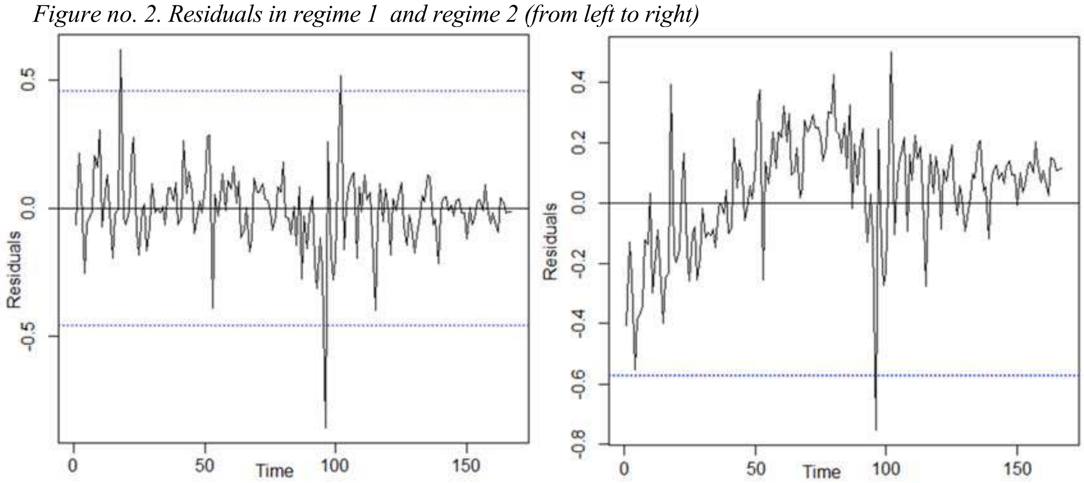
Significance codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Source: Output of the modeling the data series using the R software

For both regimes, the estimates are significant at a 0.05 significance level and the multiple R squared is very high, showing that the model explains more than 99% of the variance, in the first regime and more than 93% of the variance in the second one.

The residuals for regimes 1 and 2 are presented in Figure 2. A small variation of the residual series is noticed in both regimes.

Figure no. 2. Residuals in regime 1 and regime 2 (from left to right)



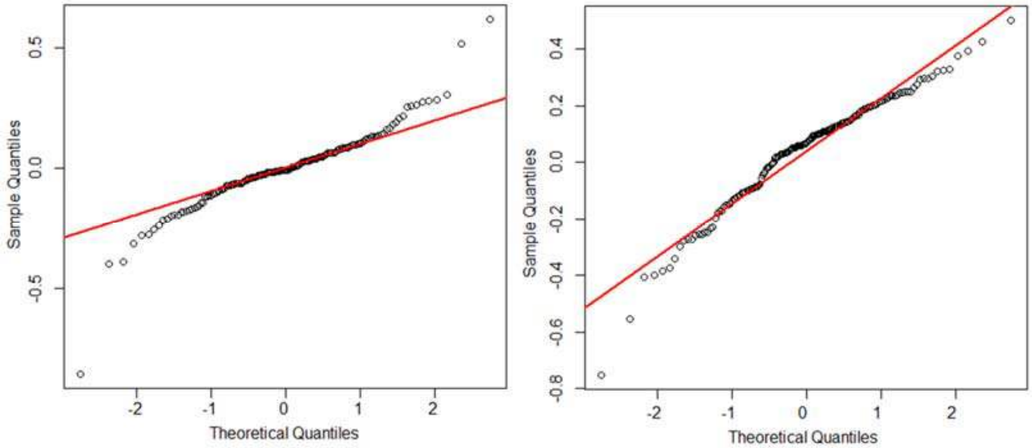
Source: Own results from the MSwM

The Q-Q plots of residuals for both regimes are presented in Figure 3. The residual series are Gaussian only for the model in the second regime (right-hand side of Figure 3).

The charts of autocorrelation (ACF) and partial autocorrelation functions (Partial ACF) of the residuals are presented in Figure 4. Whereas the residuals are not correlated in the first regime (Figure 4 (a, b), they are correlated in the second regime.

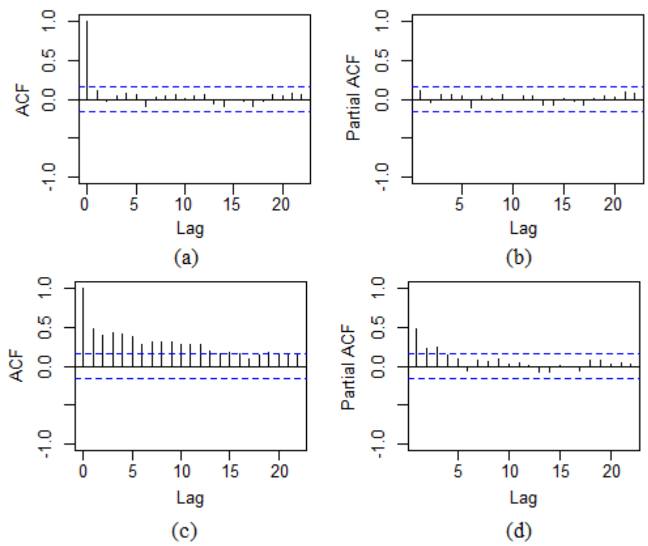
Figure 5 contains the smoothed probabilities for both regimes, while Figure 6 presents the variation of lnBET vs. the smoothed probabilities. Both prove that the model emphasizes regime changes. Significant probabilities inhomogeneity is emphasized in regime 2, where one can notice the alternation of high probabilities and very low ones. Since the majority of the probability values in the second regime are very low, it results that the system tends to remain longer in that state.

Figure no. 3. Q-Q plots for residuals in regime 1 and regime 2 (from left to right)



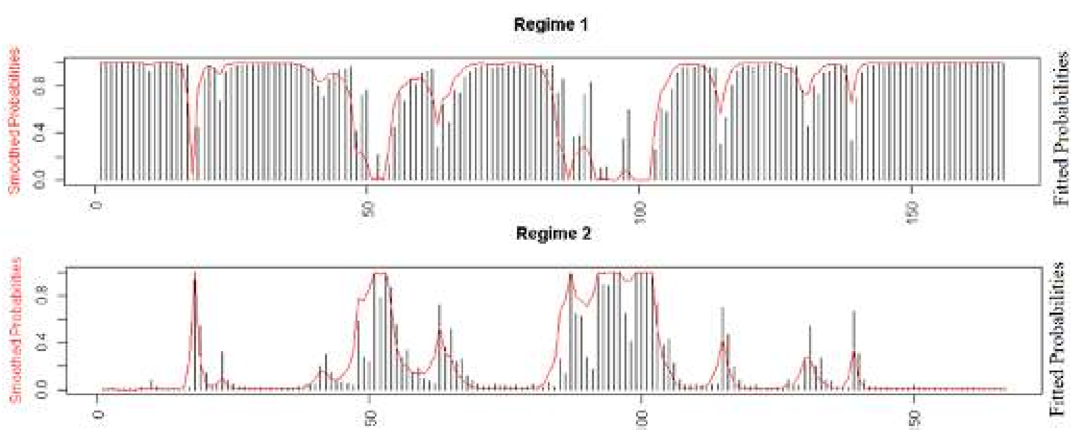
Source: Own results from the MSwM

Figure no. 4. ACF and Partial ACF plots of residuals for (a, b) regime 1 and (c, d) regime 2



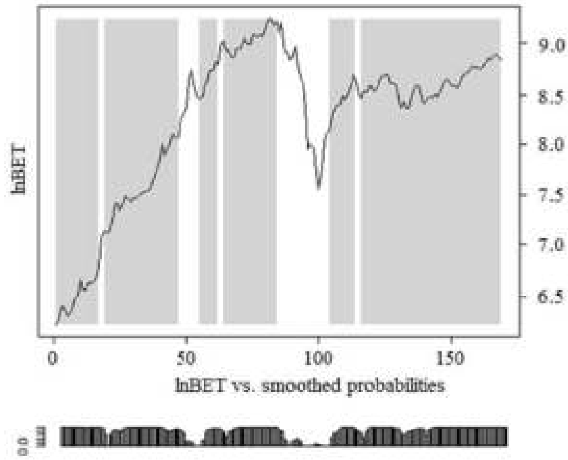
Source: Own results from the MSwM

Figure no. 5. Smoothed probabilities for both regimes



Source: Own results from the MSwM

Figure no.6. lnBET vs. smoothed probabilities for regime 1



Source: Own results from the MSwM

5. Conclusions

The MSwM model built captures the data series variability since R^2 is 0.9953, for regime 1 and 0.9322, for regime 2. Comparison of the MSwM with the GEP and hybrid models on lnBET series shows better performances of the Markov Switching Model in terms of R^2. The advantage of this kind of approach against the artificial intelligence methods is that the distinct change phases in the process evolution are emphasized. Moreover, the number of phases can be adapted function of the series complexity and the equations can be modified using, for example, second-order polynomials.

As a further study, we aim at improving the model to obtain uncorrelated residuals in both regimes and to use it in forecasting problems.

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