Markov Switching Modelling of Shocks in the Growth Regression: The Case of North Macedonia

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The empirical analysis of economic growth usually starts with the linearity assumption, implying only linear or trended movement in output growth and its relation with the explanatory variables. This is relevant when the countries under analysis follow the "Solow" balanced growth pattern, characterized by no significant fluctuations in the macroeconomic data series in the long run and usually described as variation around a single trend, which means that the variations are negligible and do not affect the linear trend in the data. However, sometimes big exogenous shocks such as Global Financial Crisis, pandemic, wars and conflicts around the World impact growth pattern, causing big shifts in growth process in the countries. This impact is especially relevant in the case of developing or transition countries, where the big shocks cause shifts in growth pattern, named growth regimes with specific properties for each regime. The growth process observed through various growth regimes instead of singular growth path was supported by the findings of many scholars who called for specification of a nonlinear data generating process for analysing the impact of big shocks on economic growth. In this paper the main objective is to examine the deviations of real economic activity, measured by the GDP growth rate from some linear trend, by the use of Markov Switching model in the case of North Macedonia. North Macedonia is good example to test for non-linearities in growth patten due to the big shocks and adjustment happening in the course of last three decades such as structural changes of transition, conflicts, Global Financial Crisis, Covid-pandemic. The results suggest that the real economic activity changes before and after some shock or regime shift occurs, characterised with specific mean growth rate and specific volatility within the regime. Hence, the conclusion is that the possible nonlinear notion of economic growth should be taken into account when conduction growth analysis, but also when defining the economic growth programmes in the countries, especially developing ones.

Keywords
Economic growth, Exogenous shocks, Markov Switching modelling, North Macedonia.

1. Introduction

One silent feature of the growth exercises is the postulation of linearity implying only linear or trended movement in output growth and its relation with the explanatory variables. This assumption is relevant when growth in developed economies is analysed, as it is usually described as variation around a single trend, which means that the variations are negligible and do not affect the linear trend in the data [1]. However, sometimes big shocks impact growth pattern, causing big shifts in growth process. This is especially the case in developing or transition countries and it can be better depicted by shifts in growth regimes due to its great instability over time. This idea was supported by the findings of many scholars who called for specification of a nonlinear data generating process [2], [1], [3]. Yet, there is no agreement among the growth researchers with respect to the empirical specification of growth nonlinearities, or with respect to the methods that should be used to distinguish growth modelling of developed and developing countries empirically. In general, in the original empirical approach, usually the business cycle researchers use a non-linear modelling approach to describe the stylized facts of business cycles, while growth researchers assume that the long-run growth of the economy follows a simple linear deterministic trend and hence use predominantly linear modelling [4]. Having in mind this division, the question arises as to whether these two concepts can be brought together for the purposes of describing volatile, non-linear growth patterns in the countries and, if so, under which circumstances? More precisely, will the concept of non-linearity borrowed from business cycle analyses be equally applicable in growth theory analyses, having the capability to capture huge shifts in macroeconomic growth paths.

It is important to note that the goal is not to examine the deviations of real activity from some linear trend. Rather the idea is to assess whether or not the real activity changes before and after some shock or regime shift occurs, when the specific combination of factors of production rather than their long-run tendency to grow governs economic dynamics [5], [6]. This contrasts with much recent work in growth literature where a linear approach to modelling is used [7], [8], [9]; and, associates much more with the business cycles literature. Although relatively new, this modelling strategy probably is more appropriate when big shocks impact to growth pattern is to be scrutinized. In addition, the validity of the selected model depends primarily on the adequacy of the empirical model as *an approximation to the data generating process* (DGP). In turn, there is the assumption of the constancy of the parameters across the observations and homogeneity of the sample [10]. This assumption is open to legitimate doubt in the growth regression context when big shocks hit one economy causing deeper structural changes or processes.

Hence, to capture non-linearity and non-regularity of growth, a within country non-linear modelling approach will be tested in the following econometric analyses, in order to achieve richer specifications for examining countries' experiences, due to shocks in contrast to recent traditional linear or panel approaches. Markov Switching models are specific non-linear models extensively employed in the analyses of the volatility, persistence and stylized facts of business cycles. Their limited use in growth analyses raises the question as to whether they can be appropriate for the analysis of growth in a particular context; namely, growth impacted by big exogenous shocks. The main objective of the applied regime switching model is to allow for multiple structural breaks in a given time series, i.e., to allow for different behaviour of the dependent variable *y* in "different states of nature", while at the same time estimating the timing of the transition from one state to another. In other words, regime switching models do not only jointly estimate the probable number (if any) and timing of regimes in the data, but they are particularly well suited to investigate whether or not different regimes posited in theory, or suggested by observation-guided or by less sophisticated forms of analysis, exist in reality and in the data generating process (DGP). This advantage makes them especially suitable for the analysis of economic growth pattern, interrupted by big shocks and shifts. In addition, Markov switching models do allow for distinctive parts of the model to depend on the state of the economy (the "regime"), potentially relaxing some or all of the restrictive assumptions of linear modelling with respect to the constant (intercept) (α_0), mean (μ), autoregressive elements (α_p), variances (σ) and included exogenous variables (X) throughout the sample period. Once again, this option is convenient for the particular research of transition or developing countries especially, because it allows for closer qualitative description of the various regimes in the empirical model of growth.

Noticeably, the tasks that Markov Switching models have in detecting regimes are highly complex and entail considerable complexity of the estimation techniques required to deal with time series data. The intuition behind the estimation technique suggests that through filtering and smoothing of the observable data y_t, numerous probabilistic inferences with respect to regime change are computed at different points throughout the sample and, lastly, the filter and smoother recursions reconstruct the time path of the regimes. In general, the procedure for calculating the probabilities is rather complex, which requires repeated iterations and numerical techniques until some convergence criterion is satisfied. Full technical explanation of the estimation techniques and of the corresponding software programmes are given by several authors [11], [12].

The aspiration to address the above questions shaped this paper. Hence, it is organized as follows. Second section gives the main theoretical background, followed by the main intuition behind non-linear modelling and the rationale for use of this approach in this research, setting out the main characteristics of Markov switching models and explaining various extensions. The methodology and the proposed model are presented in section 4. Section 5 presents the estimation results and interpretation from the univariate analysis, applied in the case of GDP growth rate of North Macedonia. The last section concludes.

2. Theoretical background

Deriving from the work of Neftçi [13] and Hamilton [5], a large literature has developed based on the Markov process to describe the underlying growth process of the economy. Although most of this literature is in the business cycles framework, offering explanations for the characteristics of business cycle changes, yet, some modelling ideas can be useful in modelling instable growth process as well, broken by the big exogenous shifts.

The pioneering work in this area began with Neftçi [13], who examined the idea that the unemployment rate displays asymmetric behaviour over various phases of the business cycle. Using a Markov process, he implemented statistical tests to see if the behaviour of the quarterly unemployment rate is characterized by sudden jumps and slower drops. His findings suggested that the probabilistic structure of the unemployment rate might indeed be different during upswings and downswings. These implications launched the introduction of the nonlinear approach to major economic time series analyses.

Later on, Hamilton [5] proposed a Markov switching model with an unobserved state to describe the phases of a business cycle. He decomposed and modelled the series into finite sequences of distinctive stochastic processes or regimes: contractions and expansions. The regimes are associated with different conditional distributions of the growth rate of real GDP where, in this case, the mean is positive in the first regime (expansion) and negative in the second regime (contraction). He started with the mean adjusted form of the MS AR, allowing for switches between two states or regimes (s1= expansion, s2=contraction).

$$\mu(s_t) = \begin{cases} \mu_1 > 0 \\ \mu_2 < 0 \end{cases} \text{if} \left| \begin{array}{l} s_1 = 1 \\ s_2 = 2 \end{array} \right.$$

Equation 1

The variance of the disturbance term $u_t \approx NID(o, \sigma^2)$ is assumed to be the same in both regimes. This model when the mean switches and the variance is equal for both regimes is referred in the literature as MS Mean (2) – AR (4) to denote 2 regimes and 4 lags. The choice of the final model and number of lags is usually based on the Akaike Information Criterion (AIC) and the Hannah-Quinn criterion (HQ) as in standard time series data techniques. Additionally, he assumes that the regime shifts are exogenous with respect to all realizations of the regression disturbance. Lately, some extensions of the MS models have been introduced to relax the assumption of exogeneity of the regime unobserved variable [14]. Kim [14] develops a model in which the latent state variable controlling the regime shifts is endogenously determined. Based on probit specification for the realization of the latent state, the model parameters are estimated via maximum likelihood with relatively minor modifications to the recursive filter [5]. Hamilton [5] concludes that once the law is specified for the states st, the evolution of the regimes can be inferred from the data.

Along similar lines, Morley and Piger [15] considered the ability of simulated data from linear and nonlinear time-series models to reproduce features in U.S. real GDP quarterly growth data (1948 -2003) related to business cycle phases. Focusing the analysis on a number of linear Autoregressive Moving Average Models (ARMA) and nonlinear Markov-switching models, they found that both linear and Markov-switching models are able to reproduce business cycle features such as the average growth rate in recessions, the average length of recessions, and the total number of recessions. However, they found that Markov-switching models perform better than linear models at reproducing the variability of growth rates in different business cycle phases, concluding that the nonlinearity of the data is important in reproducing business cycles features. One interesting point in their study is the division of the business cycles into recession and expansion, with the latter divided once more into two phases: recovery phase and a mature expansion phase. They conclude that usually high-growth recoveries follow recessions and there is a strong correlation between the severity of a recession and the strength of the subsequent recovery. Although recent experience suggests that this finding does not hold for recessions following asset price deflation and financial crisis.

This class of models has been extended to a multivariate setting [4], [12]. Krolzig [12] has applied the Markov switching approach to advanced analysis of time series data within the vector autoregression framework (called MS VAR) and Vector Equilibrium Correction Mechanism (named MS VECM). These extensions enabled reflection of the idea of a co-movement among time series, which was not possible in the univariate Hamilton framework. However, they have one important drawback, they are highly data consuming techniques. Using the three-regime Markov switching vector autoregression, models the changes in the long-run growth rate of real GDP and employment for the US, Japan and developed countries in Europe over the last four decades [12]. Using quarterly data sets, the regime identification in this paper distinguishes recession, growth and high growth; the last one associated with shifts not only in the underlying growth rate of the economy, but also in labour productivity, which reflects structural changes in the economies [4]. For example, in the case of the United States, the long expansions of recent years (i.e., before the global financial crisis and its aftermath) instead of rapid, but volatile economic recovery after recessions signify basic changes in the business cycle pattern. In the case of Japan, he identifies long episodes of rapid economic expansions (observed until the mid-1970s) in addition to the cycle of economic expansions and relatively long economic recessions (as in the 1990s). In Europe, the third regime of high growth corresponds, essentially, to the behaviour of the Southern European economies at the beginning of the sample period and the process of catching up in the 1970s in Europe. As a result, he draws an important inference from these models:

These economies have been subject to structural change manifested in the form of structural breaks, i.e. permanent large shifts in the long-run mean growth rate of the economies, and persistent changes in the volatility of the growth process. The study of these phenomena, which are distinctively different from a reoccurring cycle of expansions and recessions constituting the business cycle, requires allowing for … a multi-regime, possibly integrated-cointegrated multiple time series model, in which the empirical evidence can be established for the presence of common nonlinear business cycles and structural change. The significance drawn from the empirical evidence leads to a critique of traditional separation of the assessment of the business cycle and economic growth [12, p.12].

Jerzmanowski [21] has built on Pritchett's observations on growth regimes and he characterized various growth regimes and the countries' transitions among them using a Markov-switching regression using cross-country data for 89 countries over a period of 1962-1994 on growth rates of output per worker from the Penn World Tables 6.1. He estimated four distinct regimes corresponding to four growth processes.

- A stable growth regime corresponds to the growth experience predominant among developed economies, with long-run average growth of about 2 per cent and low growth volatility.

- A stagnation regime is characterized by no growth on average and larger volatility of growth shocks. In this regime, periods of growth and decline occur but are not very persistent.
- He also identified a separate regime of one-time large shocks to growth, claiming that while these shocks tend on average to be negative reflecting economic crises, the dispersion is very large and positive shocks are possible. However, he found that these shocks have no persistence.
- Finally, he identifies a regime of fast, miracle-like growth with an average long-run growth of 6 per cent.

Following the suggestions from the literature, the Markov Switching modelling will be applied in the following analyses, applying the simplest univariate Markov switching model, that is at the same time the least data consuming model. The main idea is to focus the empirical analysis on the identification of the shifts and structural changes in growth pattern; indeed, within the limits imposed by the reconciliation between the relatively short data series available and the data requirements of the advanced Markov Switching models.

3. Markov Switching Models

The rather general formulation of the Markov Switching Model allows for a great variety of particular Markov switching regression specifications, which have different notation depending on the parameters conditioned on the state s_t in each model. The most appealing notation of the various MS models is due to Krolzig [4] where: *I* denotes the Markov switching intercept term, *M* stands for Markov switching mean, *A* – Markov switching auto-regression parameters and *H* - Markov Switching heteroscedasticity.

The most famous MS - Autoregressive model (MS-AR) is the model defined by [5] which allows for a random shift in the mean level of the process through a two-state hidden Markov chain. Hence, the Equation takes the following form:

Equation 2 $$y_t - \mu(s_t) = \alpha_1(y_{t-1} - \mu(s_{t-1})) + ... + (\alpha_p(y_{t-p} - \mu(s_{t-p})) + u_t\,,$$

$u_t \sim N(0, \sigma^2)$

where the terms $\mu(s_t)$ denotes the mean of the series (dependent on the specific regime (s_t)), α_p denote the autoregressive parameters and p is the lag.

Frühwirth - Schnatter [16] suggests that in Equation 2 there is an immediate one-time jump in the process mean moving from one regime to another. Hence, this model is the MSM (Markov Switching Mean) Model. As noticeable from the equation, the present value of (s_t) as well as a limited number of past values $s_{t-1,} ..., s_{t-p}$ influence the observation density of y_t throughout the means in various regimes.

McCulloch and Tsay [17] proposed an alternative model by introducing the hidden Markov chain into Equation 2, assuming that the intercept is driven by the hidden Markov Chain rather than the mean level. Given this, the specification can be expressed as:

Equation 3 $$y_t = \alpha_0(s_t) + \alpha_1 y_{t-1} + ...\alpha_p y_{t-p} + u_t\,, \qquad u_t \sim N(0, \sigma^2)$$

In this model, the intercept α_0 is the parameter that experiences a sudden jump in different regimes (s_t), which changes the mean level of the series rather indirectly, approaching the new value smoothly over different regimes. In this case, only the present value of (s_t) influences the observation density of y_t. In Krolzig's terminology [12], this is the MS Intercept (MSI) model.

Additionally, [4] notes that if the order of autoregression is zero, then the MSI (Intercept) and MSM (Mean) specifications are equivalent. In Equation 2 and Equation 3 if all α_p terms are equal to zero, then $y_t - \mu(s_t) = u_t$ will equal $y_t = \alpha_0(s_t) + u_t$. Hence, the regime specific intercept term will present the regime specific mean of the series $\mu(s_t) = \alpha_0(s_t)$.

The equality of the intercept term and the mean of the series is one technical advantage of this simple Markov Switching specification (without autoregressive parameters) that will be of interest for this research, because it allows tracking the switches and volatility in the mean level of the growth series.

Additionally, one supplementary advantage of this simple specification with no autoregression is related to the fact that the observation density of y_t is only influenced by the present value of (s_t). In other words, history is not allowed to be "memorized" in the regime variable, which is an appropriate assumption for the analysis of big shocks impact on growth pattern. Hence, capturing the events as they happened might be more appropriate.

In more general form, MSAR also allows for the autoregressive parameters to be governed by the s_t, switching between the states and introducing different dynamic patterns in various states, such as fast fall and slow recovery in business cycles [11].

Equation 4 $$y_t = \alpha_0(s_t) + \alpha(s_{t,1})y_{t-1} + ...\alpha(s_{t,p})y_{t-p} + u_t, \qquad u_t \sim N(0,\sigma^2)$$

All parameters are the same, only in this equation, the autoregressive parameters $\alpha(s_{t,p})$ have the switching dimension.

[18] proposed a class of MS models in which the regimes switch with underlying (economic) fundamentals. In order to capture the fundamentals, different models include various explanatory variables within different MS specifications. One general specification can be derived as an extension of the MSI model:

Equation 5 $$y_t = \alpha_0(s_t) + \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + \beta x_t + u_t, \qquad u_t \sim N(0,\sigma^2)$$

where β represent the coefficients on the exogenous x_t variables, which can depend/or not on (s_t) and the rest of the parameters are the same.

The MS -VAR and MS –VECM applications analyse the co-movement between several mutually dependent variables and the tendency of some variable(s) to move before others in a system [6] [4]. The mean adjusted form of the MS-VAR is given by the formula:

Equation 6 $$y_t - \mu(s_t) = A_1(s_t)((y_{t-1} - \mu(s_{t-1})) + ... + A_p(s_t)((y_{t-1} - \mu(s_{t-p})) + u_{Kt},$$

$$u_t \sim N(0,\sigma^2)$$

where $y_t = (y_{1t},...y_{Kt})'$ is a set of K time series variables, A_1 is a (KxK) coefficient matrix, one for each lag *(p)* of the variables (dependent on s_t) and $u_t = (u_{1t},....,u_{Kt})'$ are the unobservable error terms [12].

In any of the above models, the variance may be assumed constant, or it might be possible to assume a shift in the variance, such that $u_t \sim N(0,\sigma^2_{u,s_t})$.

In practice, modelling a time series by a Markov Switching Model requires some specification or hint on the number of expected states of the hidden chain. Then, the state specific parameters and transition matrix are estimated from the data (such as the variances of the error term σ^2, the autoregressive coefficients α_1, the intercepts α_0 and the state probabilities p_{ij} for different regimes). Results from estimation are accompanied by measures of the persistence of regimes and the expected number of periods (years, quarters, months) for each regime.

4. Proposed model

The primary objective of this paper is to discover if and how GDP growth regimes have changed in North Macedonia, using the following general and estimable form of the model is specified:

Equation 7 $$y_t = \alpha_0(s_t) + \sum_{j=1}^{p} \alpha_j(s_{t-j}) y_{t-j} + u_t(s_t) \ , \qquad u_t \sim N(0, \sigma^2)$$

where j is the lag and p is the number of lags introduced, y_t is the observable variable, $\alpha_0(s_t)$ is the regime specific intercept, $\alpha_j(s_{t-j})$ is the autoregressive parameter and $u_t(s_t)$ is the regime specific variance. Although usually an autoregressive model, [4] introduces y_t as an MSI (2)[1] – AR(0) process, meaning that the whole autoregressive term is dropped. As mentioned, all relevant information about the future of the Markovian process is included in the present state, where the past and additional variables such as y_t reveal no relevant information beyond that of the actual state [4]. Additionally, in this model the intercept also represents the mean of the series under analysis. Hence,

Equation 8 $$y_t = \alpha_0(s_t) + u_t(s_t)^{2}$$

where the white noise process can be either homoscedastic, that is $u_t \sim N(0, \sigma^2)$ or it can be heteroskedastic (the variance of the error term being regime dependent), that is $u_t \sim N(0, \sigma^2{}_{(s_t)})$.

In most studies, the data used in the analysis are the log levels of GDP transformed into first differences [6] [19]. As y_t denotes the growth rate of GDP, and it is assumed that the process for y_t is a univariate dynamic regression with regime switches, the model may be written as follows:

Equation 9 $$\%\Delta GDP_t = \alpha_0(s_t) + u_t(s_t) \ , \ u_t \sim N(0, \sigma_{s_t}{}^2)$$

In Equation 9 the intercept term α_0 and the error term u_t depend on s_t. The switching variance is supposed to capture the changing volatility in various regimes.

The presented modelling strategy departs from the standard business cycles application of Markov Switching Models. Namely, the omission of the autoregressive elements in the regression, together with allowing for more regimes than are usual in business cycles studies, marks a difference between the present research approach and most business cycles studies.

The data used is ln (GDP level), which is actually first difference of GDP, which ensures stationarity of data series taken from the World Development Indicators databank [20].

5. The results

After comparison of the competing MSM and determining the preferred model, the preferred model's estimation results for North Macedonia results are presented in the following Table below. The results, estimated by the use of OxMetrics are accompanied by:

- The estimated regime-specific intercepts of the series (Constant (s_t)) (section 1 in the table). Each coefficient indicates the country's mean growth rate for a specific regime, which is determined by the data generating process.
- The regime standard deviation (Sigma (σ_t)) (section 2 in the table) is the next indicator that is used to measure GDP growth rate volatility within specific regimes for each country.
- The durations of each regime (D(s_t)) for each country, accompanied by the exact periods given in years in the brackets (section 3 in the table). These indicators also present valuable information on the duration of each of the regimes in concert with its volatility and mean GDP growth rate. In addition, it enables identification of the possible downturns in the countries due to shocks.
- In addition, finally, the persistence of each regime (section 4 in the table) which indicates the stability of each regime.

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[1] In Krolzig's terminology, the abbreviation MSIH stands for Markov Switching Intercept Heteroscedastic model.

- In section 5 of the table, also the LR test is reported with modified critical values; accompanied by the diagnostic tests (section 6).

Table 1 Estimation results from Markov switching model for North Macedonia

Various estimated coefficients		**Intuitive explanation of the estimated coefficients**
Constant(0) **Constant(1)** **Constant(2)**	-3.7 (0.014)** 1.02 (0.000)* 4.05 (0.000)*	Mean growth rate for the specif regime (in percent)
Sigma (0) **Sigma(1)** **Sigma(2)**	2.8 (0.024)** 0.4 (0.001)* 0.9 (0.006)*	GDP growth rate volatility within a regime
D(0)	8 years	
D(1)	8 years	
D(2)	15 years	
Regime 0 **Regime 1** **Regime 2**	0.66 0.32 0.75	Persistence of the regime (stability)
LR test	Chi^2(8) = 40.740 [0.0000]* approximate upperbound: [0.0000]*	LR-tests show that linear specifications rejected
Normality test: **ARCH 1-1 test:** **Portmanteau(4):**	Chi^2(2) = 0.64379 [0.7248] F(1,9) =0.0052987 [0.9436] Chi^2(4) = 7.6918 [0.1035]	

Note: * - significant at 5% of significance, ** - significant at 10% level of significance

The graph bellow shows graphically the growth pattern of North Macedonia, which has experienced four separate cycles of repeating regimes. Each cycle starts with low growth rates and high volatility (Regime 0, marked in blue), followed by the recovery growth path with moderate growth rates and still high volatility (Regime 1, marked in grey) and lastly the high growth path with lowest volatility (Regime 2, marked in yellow). Hence, each cycle consists of three consequent regimes (Regime 0, 1 and 2) repeating consequently.

- As can be seen the first cycle starts with the start of transition with huge drop of -3.7 per cent annual growth rate and volatility of 2.8 per cent till 1995 (first blue in the marked area), followed by the second regime of moderate annual growth of 1.02 per cent and volatility of 0.4 per cent till 1997(first grey area), and then a period of high growth marked in yellow (first yellow area) characterised by an annual growth rate of 4.5 per cent and volatility of 0.9 per cent lasting till 2001, i.e. until the internal ethnical conflict started.
- The country again falls into the first and then second regime for a year each time, to continue in relatively high growth regime after 2003 (second pair of blue, grey and yellow areas).
- The depiction repeats once again with the drop in 2009 and moderate recovery in 2010 as a result of the impact of the Global Financial Crisis (third complex of blue, grey and yellow areas). Afterwards, after 2013 the country goes into high growth regime until the pandemic of 2020.
- The last cycle starts with the big fall in the economic activity due to the pandemic shock in 2020. Fast recovery the following year captures the final year for which data are available.

- The persistence indicator, i.e. transition probability of the system to stay within the regimes is lowest for regime 1 (0.32), while it is much higher for the first and third regime - 0.66 and 0.75 - respectably.

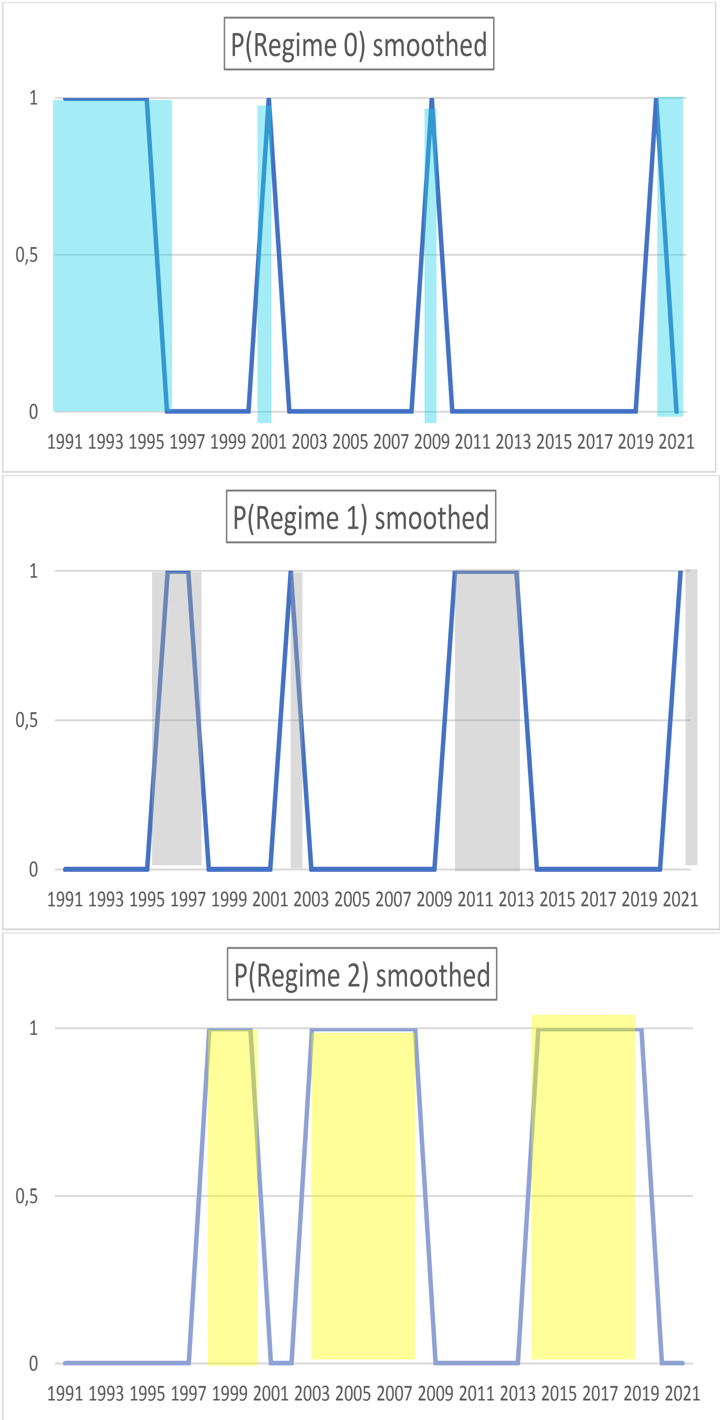

Figure 1 Graphical presentation of the regimes

It should be mentioned that while informative about the dynamic of development under big shocks, univariate MS analysis reveals nothing about the causal mechanisms. Nevertheless, even with this remark in mind, the univariate analysis of GDP growth rates only, reveals that growth pattern has been broken and within each regime, specific paths with distinctive characteristics and volatility occurred. The regime specifications are presented in the following Figure 2.

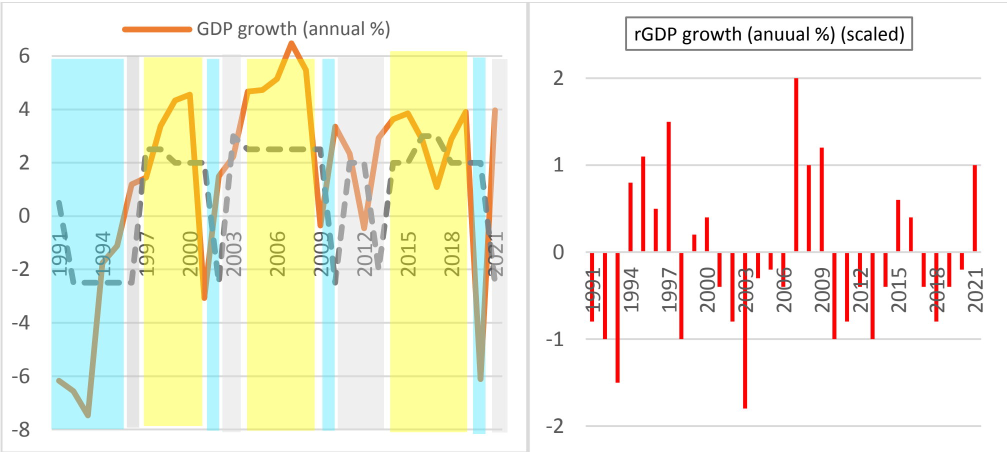

Figure 2 Regime specification on the GDP growth pattern of North Macedonia

Paradoxically, the appropriate modelling strategy to capture switches between stages or regimes of growth was borrowed from business cycle theories. Although business cycle theory is not an appropriate framework for analysing growth in transition, the review of business cycle analyses indicated that possible empirical solutions for capturing both the instability - hence, breaks – *between* growth regimes and, at the same time, the volatility of growth *within* growth regimes can be found in nonlinear econometric models, Markov Switching Models in particular. After assessing the applicability of non-linear models in the case of North Macedonia, the main findings suggested that the country moved from one to another regime according to the data generating process. Namely, the first regime is characterised by the largest drop and highest volatility as compared to other regimes; the second regime is a sort of stabilisation regime with increasing GDP growth rates and falling volatility; and the third regime is characterised by the highest GDP growth rates and the lowest volatility as compared to the previous regimes. Additionally, this analysis showed that volatility of growth was also an important feature of economic growth that possibly determined the further success of moving into next regime, with it being the highest in the first regime and comparably lower in the next two regimes.

Conclusion

In summary, the univariate analysis by the use of GDP growth rate and MS modelling has enabled closer assessment of the peculiar characteristics of growth - instability and volatility - in the case of North Macedonia. Firstly, the estimation results, then, the analysis of the graphical presentation offer evidence in favour of the assumption of non-linear growth and the corresponding existence of various regimes or stages that happen due to shocks.

Furthermore, the benefit of the empirical procedure is that the switches between regimes are easily visible and identifiable, which, in turn, again confirms the idea of switches of regimes among countries in contrast to the smooth linear growth process assumed in the growth studies. Finally, the model is not far away from the actual real GDP growth data. It represents them relatively well, at the same time connecting our theoretical model with the empirical results from the real data sets.

However, the question arises as to whether this framework can be extended to investigate if the regimes identification persists when the main driving forces behind different transition stages or regimes are introduced? Or in simpler terms, what drives the switch to a higher regime for one country? In order to do so, the further avenues for research should extend the applied Markov Switching Model by introducing multivariate analysis.

References

1. Pritchett, L. (2000). Understanding Patterns of Growth: searching for hills among Plateaus, Mountains and Plains. The World Bank Economic Review, Vol.14(2), pp. 221-250.
2. Durlauf, S.N. & Johnson, P.A. & Temple, J.R.W. (2004). Growth econometrics. Working papers 18, Wisconsin Madison - Social Systems. Available from: http://irving.vassar.edu/faculty/pj/growtheconometrics.pdf
3. Easterly, W., Islam, R. & Stiglitz, J.E. (2000). Shaken and Stirred: Explaining Growth Volatility in Pleskovič, B. and Stern, N. (eds.) Annual World Bank Conference on Development Economics 2000 The World Bank.pp.191-212
4. Krolzig, H-M. (1998) Econometric Modelling of Markov-Switching Vector Autoregressions using MSVAR for Ox Institute of Economics and Statistics and Nuffield College, Oxford. Available from: http://fmwww.bc.edu/ec-p/software/ox/Msvardoc.pdf
5. Hamilton, J. (1989). A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. Econometrica. Vol.57, pp. 357-384.
6. Hamilton, J. (2005). Regime Switching Models prepared for Palgrave Dictionary of Economics, paper assessable on internet: http://www.ressources-actuarielles.net/EXT/ISFA/1226.nsf/769998e0a65ea348c1257052003eb94f/a54fe3a4a8b85e47c125761200700885/$FILE/palgrav1.pdf
7. De Melo, M., Denizer, C., Gelb, A. & Tenev, S. (2001). Circumstance and Choice: The Role of Initial Conditions and Policies in Transition Economies, World Bank Econ Review. Volume 15 (1): 1-31. doi: 10.1093/wber/15.1.1
8. Havrylyshyn, O &Van Rooden, R., (2000). Institutions Matter in Transition, but so do Policies. IMF Working Paper, (March 2000) pp. 1-28, 2000. Available at SSRN: http://ssrn.com/abstract=879570
9. Fischer, S. & Sahay, R. (2004). Transition Economies: The Role of Institutions and Initial Conditions. IMF, paper presented at Calvo Conference- April 14, 2004.
10. Hendry, F. D. & Krolzig Hans – M. (2004). We run One Regression. Oxford Bulletin of Economics and Statistics, 66, 5 (2004) 0305-9049
11. Bruce, M. & Watkins J. (1998). A Markov Switching Cookbook. Departmental Working Papers 199817, Rutgers University, Department of Economics. Available from: ftp://snde.rutgers.edu/Rutgers/wp/1998-17.pdf [Accessed: Jan 2013]
12. Krolzig H-M. (2000). Business Cycle Measurement in the Presence of Structural Change: International Evidence. Department of Economics and Nuffield College, Oxford University, Available from: http://www.nuff.ox.ac.uk/economics/papers/2000/w33/ijf.pdf[Accessed: [Jan, 2013]
13. Neftçi N. S.(1984). Are Economic Time Series Asymmetric over the Business Cycle?. Journal of Political Economy, Vol.92 (2). pp. 307–328
14. Kim, C.-J. (2004). Markov-switching models with endogenous explanatory variables. Journal of Econometrics. Vol. 122, Issue 1, Sep. 2004, pp. 127–136.
15. Morley J. & Piger, J. (2005). The Importance of the Nonlinearity in Reproducing Business cycle Features. Federal Reserve Bank of St. Louis. Working paper 2004-032B; Available from: http://research.stlouisfed.org/wp/2004/2004-032.pdf
16. Frühwirth-Schnatter, S. (2006). Finite Mixture and Markov Switching Models. New York: Springer.
17. McCulloch, R.. & Tsay, R.(1994). Statistical analysis of economic time series via Markov switching models. Journal of Time Series Analysis.Vol. 15 (5). pp. 523–539, September 1994
18. Diebold F., Gardeazabal, J. & Yilmaz, K. (1994). On cointegration and exchange rate dynamics. Journal of Finance No.49, pp. 727-735.
19. Altuğ, S. & Bildirici, M. (2010). Business Cycles around the Globe: A Regime Switching Approach. Working Papers 0032, Yildiz Technical University, Department of Economics, revised Mar 2010.
20. World Bank. (2012). World Development Indicators. ESDS International, University of Manchester.

21. Jerzmanowski, M. (2006). Empirics on Hills, Plateaus, Mountains and Plains: A Markov-switching Approach to Growth. Journal of Development Economics. Vol.81, pp. 357-385.