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MODELLING RETURN AND VOLATILITY IN EMERGING STOCK MARKETS: A MARKOV SWITCHING APPROACH

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ABSTRACT

This paper studies stock market time-varying performance in a Markov environment between four emerging Balkan stock markets, namely, Turkey, Romania Croatia and Bulgaria, and two developed markets, the U.S. and Greece. We employ: (a) an exogenous Markov regime-switching methodology where the time variation of returns is modeled to capture short-term dynamics; (b) a Markov switching vector autoregression methodology to model jumps in volatility regimes. Our findings provide evidence on time-varying return dependence and volatility regime linkages between Balkan and developed stock markets.

JEL: C22, G11, G15.

Keywords: Markov switching, Volatility regimes, Equity market integration, Balkan stock markets

INTRODUCTION

Extensive interest in time-varying parameter models of financial time-series has been observed during the last decade. Since the influential research of Engle and Granger (1987), the estimation of long-run relationships among economic variables using cointegration methods has received much attention. The important aspect of using cointegration methods is to keep the information variables provided by nonstationary variables without differencing. The most important underlying assumption behind the usual cointegration methods relies on the stability of long-run relationships. Several studies have attempted to model relative equity market performance using cointegration, aiming to identify a long-run equilibrium relationship to which individual indices can be expected to converge towards over time[1].

Equity market integration has strong implications on investment decisions and portfolio diversification (Kasa, 1992; Cohrey *et al.*, 1993). The existence of a common trend implies high cross-market correlations, diluting any potential diversification benefit over the long-term. However, the long-run stable equilibrium relationships conjectured by Johansen (1988) and Engle-Granger (1987) techniques are not suitable for modeling the dynamic process of stock market integration, since these are incomplete and continue to exhibit strong variations over time. According to Kim *et al*., (2005), the existence of an equilibrating process only and not the driving forces behind the long-run equilibrium are investigated applying the standard cointegration techniques.

Non-linear cointegration techniques have recently been developed by Gregory and Hansen (1996), Breitung and Gourieroux (1997), Breitung (2001), and Davies (2005). Gregory and Hansen (1996) investigate a non-linear shifting regime regression which takes into account the possibility of instability in long-run relations, allowing for structural breaks. Their test detects several equilibrium relations omitted by the conventional cointegration testing procedures, showing that long-run relations do not cease after a structural change has occurred.

The Markov switching framework has been also applied successfully to model return of well-developed stock markets by Hamilton and Li (1996), Schaller and Norden (1997), among others[2]. Moreover, Davies (2005) examines the degree of international equity market integration using regime-switching cointegration allowing for structural breaks. Volatility clustering and mean reversion are well tested through the application of the Markov approach (e.g., Dewachter, 2001; Ang and Bekaert, 2002; and Jeanne and Rose, 2002).

On the other hand, the Markov Switching Vector Autoregression model (MS-VAR) is the most suitable to model volatility when the data generating mechanism incorporates exogenous structural change subject to shifts in the deterministic factors. The MS-VAR has been proposed as an alternative to the constant parameter, linear time-series models of the earlier Box and Jekins (1970) modeling transition. It was introduced by Krolzig (1997) as a multivariate generalization of the Markov switching autoregressive model.

The purpose of this paper, is to contribute to the equity market integration literature applying a Markov regime-switching methodology (allowing for structural breaks) and the MS-VAR approach, to model Balkan stock markets time -varying return and volatility, during the period 2000-2006. These models are able to detect several equilibrium relations omitted by the conventional cointegration testing procedures. Moreover, we use exogenous latent variables to model Balkan markets return and volatility. Particularly, we set both Greece and U.S.A as exogenous variables affecting the Balkan markets. Our results provide evidence on time-varying return dependence and volatility regime linkages between Balkan and developed stock markets.

The motivation for this research derives from the significant performance of the Balkan economies the last few years, in terms of income per capita and international competitiveness. In these countries, the major improvements are focused on macro-stabilization, price and market liberalization (including international trade), restructuring and privatizing state enterprises (IMF, 2005). Among the Balkan stock markets, Romania, Bulgaria, Turkey and Croatia are considered the most developed, in terms of capitalization, turnover and number of traded securities. On the other hand, Greece is the only EU member state in Balkan rezgion and the key leading player, while U.S.A. is considered the world's dominant economy and the "foreign global influence". Finally, there is no other study in the existing literature modeling emerging Balkan markets return and volatility to the best of our knowledge.

The structure of the paper is organized as follows: Section II analyzes the Markov Regime Switching process. Section III discusses the Markov Switching Vector Autoregressive model. Section IV presents the data, while empirical results are reported in Section V. Finally, Section VI contains the concluding remarks.

MARKOV REGIME SWITCHING PROCESS

The regime switching model applied in this study is based on Hamilton (1989), Kim *et al*., (2005), and Davies (2005). Initially, we consider the following Gaussian regime-switching model for the sample path of a time series, $\{y_t\}_{t=1}^{T}$:

$$y_t = x'_\tau \beta_{st} + x''_\tau \beta_{st} + \sigma(s_t)\,\varepsilon_t \qquad \varepsilon_t \sim \text{i.i.d. } N(0, 1) \tag{1}$$

where, y_t is an $I(1)$ non stationary variable (Balkans market return) and is scalar, x'_τ is a $(k \times 1)$ vector of observed exogenous or predetermined explanatory variables (in our case the return of the U.S. stock market), x''_τ is a $(k \times 1)$ vector of observed exogenous or predetermined explanatory variables (in our case the return of the Greek stock market), σ is the variance and $s_t = i$ is the state variable. We expect time variation assuming that the series follows a stochastic process. Hence, mean return, variance, and serial correlations of stock market returns depend on the regimes, s_t. We denote the number of regimes by N, so that $i = 1, 2, \ldots, N$. We deal with the case where $N = 2$, in order to allow for two structural breaks.

The foundation for modelling the Balkan stock markets is that deviations from uncovered interest parity (UIP) are predictable. To create a sufficient structure for the expected deviation from UIP, we modify the traditional Markov model as a function of two Markov switching state variables in the conditional mean, adopting Davies (2005) approach.

Cointegration across the $I(1)$ variables contained in eq. (1) implies that there is non stationarity in levels and stationarity in the first differences. Particularly, shocks in the level of an $I(1)$ series are permanent whereas shocks to the first difference are transitory. ADF test is utilised to test for the $I(1)$ property. The exact stochastic process of the discrete multi-period regimes s_t following a first order Markov chain depends on the order of the process for the one-period regimes S_t and on the number of its actual states N.

The state variable in our case is unobserved and is assumed to evolve according to a Markov chain with transition probabilities[3]:

$$P(S_t = i / S_{t-1} = j, Z_t) = P_{i,j}(Z_t) \tag{2}$$

We assume the Markov process is stationary, with unconditional probabilities:

$$P(S_t = i / \bar{z}) = P(S_t = i / \bar{z}), \forall_t^2$$

$$S_t = \begin{Bmatrix} 1 \text{ if } & \eta_t < (\alpha_{St-1} + Z'_\tau b_{St-1}) \\ 2 \text{ if } & \eta_t \geq (\alpha_{St-1} + Z'_\tau b_{St-1}) \end{Bmatrix} \tag{3}$$

$\eta_t \sim$ i.i.d. $N(0, 1)$.

In eq. (3), the transition probabilities are influenced by a $(q \times 1)$ vector of observed exogenous or predetermined variables Z_t, where Z_t may include elements of x_t. Also, the Markov chain is assumed to evolve independently all observations of those elements of x_t, not included on Z_t. The transition probabilities from state j to state i are then:

$$P_{i,j}(Z_t) = P(\eta_t < (\alpha_j + Z'_\tau b_j)) = \Phi(\alpha_j + Z'_\tau b_j), \tag{4}$$

$$P_{i,j}(Z_t) = P(\eta_t \geq (\alpha_j + Z'_\tau b_j)) = 1 - \Phi(\alpha_j + Z'_\tau b_j), \tag{5}$$

where, Φ is the standard normal cumulative distribution function. The transition probabilities are constrained to be in [0, 1] using a probit specification for s_t, so that $s_t \in \{0, 1\}$ in order to have two discrete one period states.

The estimator used to obtain the error term ε_t in eq. (1) is the Markov switching estimator introduced by Hamilton (1989). Model (3) considers the possibility of multiple switches in the long-run cointegrating relationship. Modifying the approach of Hamilton (1989), residuals take the following two regime Markov form:

$$y_t = \begin{Bmatrix} \beta'_1 x_t + \varepsilon_t & \text{if} \quad s_t = 1 \\ \beta'_2 x_t + \varepsilon_t & \text{if} \quad s_t = 2 \end{Bmatrix} \tag{6}$$

with the regime switching residuals calculated as:

$$\hat{\varepsilon}_t = \left\{ y_t - [\hat{\beta}'_1 \chi_\tau (\Pr(s_t = 1 \mid I_t)) + \hat{\beta}'_2 x_t (\Pr(s_t = 2 \mid I_t))] \right\} \tag{7}$$

where, $\Pr(s_t = 1 \mid I_t)$ refers to the probability of being in regime 1 conditional on information set I_t (i.e. conditional event probability). According to the Markov switching model, an unobservable latent variable drives the switching behaviour of the long-run data generation process. Since the variable responsible for the specific regime is unobservable, it is only possible to infer the likelihood of being in a specific regime at a given point in time. We employ the Markov switching estimator in eq. (6) to the levels relationship across individual equity indices.

According to Gabriel *et al*., (2002) and Davies (2005), regime switching techniques can be used to obtain stationary error correction terms where the sample is subject to multiple breaks. In the case of Markov switching residuals, they examine that tests for cointegration can be carried out using standard residual based tests even though those residuals have been obtained from a nonlinear regime switching procedure.

Having obtained the residual term $\hat{\varepsilon}_t$ using eq. (7), we estimate the following error correction model:

$$\Delta y_t = \sum_{i=1}^{n} \gamma_i \, \Delta y_{t-i} + \sum_{i=1}^{n} \delta_i \, \Delta x_{t-i} + \alpha \hat{\varepsilon}_{t-1} + e_t \tag{8}$$

where, the estimated coefficient α on the lagged residual has the interpretation of an error correction coefficient. The size of α determines the speed of adjustment back to the equilibrium relationship.

MARKOV SWITCHING VECTOR AUTOREGRESSION MODEL (MS-VAR)

One of the puzzles associated with the forecasting performance of non-linear time series models including regime-switching models, is that, when compared to linear models, a superior in sample fit does not result in superior forecasts (Clements and Krolzig, 1998; and Dacco and Satchell, 1999).

Like other regime-switching models, the MS-VAR model is a vector autoregressive process of the observed time series vector $y_t = \{y_{1,t}, \ldots, y_{k,t}\}'$, whose parameters are, at least partly, unconditionally time-varying but constant, when conditioned on an unobservable discrete regime variable $s_t \in \{1, \ldots, M\}$.

We apply the MS-VAR approach, following Kanas (2005), who explored the issue of volatility regime linkages between the Mexican currency market and six emerging equity markets. We test for the null hypothesis of no volatility regime with the following equation[4]:

$$e_t = \alpha_e + \sum_{k=1}^{l} \alpha_{e,e,k} e_{t-k} + \sum_{k=1}^{l} \alpha_{e,c,k}^{\;M} c_{t-k}^{M} + \sum_{k=1}^{l} \alpha_{e,c,k} c_{t-k} + \sum\nolimits^{1/2} (s_t)\, u_{e,t} u_{e,t} \sim N(0,1)$$

$$c_t^M = \alpha_c^M + \sum_{k=1}^{l} \alpha_{c,c,k}^{M} e_{t-k} + \sum_{k=1}^{l} \alpha_{c,c,k}^{M,M} c_{t-k}^{M} + \sum_{k=1}^{l} \alpha_{c,c,k}^{M} c_{t-k} + \sum\nolimits^{1/2} (s_t) u_{c,t}^{M,} u_{c,t}^{M,} \sim N(0,1) \tag{9}$$

where, e_t is the log equity index of each Balkan market, is the log of a developed equity market (exogenous), c_t is the log of the second developed equity market (exogenous), s_t is an unobserved regime variable, and u_t is the innovation process with a regime dependent variance covariance matrix $\Sigma(s_t)$.

Thus, our regime dependence results are conditioned upon the two exogenous variables of the developed equity markets, which may exercise an effect upon each emerging Balkan market. The regime s_t follows a Markov process defined by the transition probabilities $p_{i,j}$. Again, we consider our model with two regimes. The transition probabilities $p_{i,j}$ are:

$$p_{i,j} = \Pr(s_{t+1} = j \mid s_t = i), \; \sum_{j=1}^{2} p_{i,j} = 1, \quad \forall i, j \in \{1, 2\}. \tag{10}$$

Then, we test the volatility regime dependence through a univariate model. Specifically, we test if the high (low) volatility regime of the developed markets is independent of the high (low) volatility regime of the emerging Balkan markets. To test the null hypothesis of independence, we estimate a univariate model for each Balkan equity market of the form:

$$\Delta e_t = \alpha_e + \sum_{k=1}^{l} \alpha_{e,k} + \sum_{k=1}^{l} \alpha^M_{c,\kappa}\, \Delta c^M_{t-k} + \sum_{k=1}^{l} \alpha_{c,k}\, \Delta c^M_{t-k} + \sum^{1/2} (s_t) u_t, \quad u_t \sim NID(0,1) \quad (11)$$

where, Δ is the first difference of each series, since there exist at least one unit root in all series.

For each developed market, we estimate the following univariate model:

$$\Delta c^M_t = \alpha_{c^m} + \sum_{k=1}^{l} \alpha'^M_{c,k} \Delta c^M_{t-k} + \sum_{k=1}^{l} \alpha'_{e,\kappa} \Delta e_{t-k} + \sum_{k=1}^{l} \alpha''_{c,k} \Delta c_{t-k} + \sum^{1/2} (s_t) u_t, \quad u'_t \sim NID(0,1) \quad (12)$$

From eq. (11) we obtain the $T \times 1$ vector of the smoothed probabilities that the equity market is in the high (low)-volatility regime, i.e. $P^e_{2,t}$. Similarly, from eq. (12), we obtain the $T \times 1$ vector of probabilities that the Balkan equity market is at the same level of volatility regime, i.e. $P^c_{2,t}$. Following Kanas (2005), if the volatility regimes of the two markets are independent, then the probability that both markets are jointly in the high (low)-volatility regime, i.e. $P^{c,e}_{2,t}$, should be equal to the product of the probability that the developed equity market is in the high (low)-volatility regime and the probability that the Balkan equity market is in the high-volatility regime. Thus, the null hypothesis of independence is:

$$P^{c,e}_{2,t} = P^e_{2,t}\, P^c_{2,t}, \qquad \forall t = \{1, \ldots, T\} \quad (13)$$

with the alternative of dependence being $P^{c,e}_{2,t} \neq P^e_{2,t}\ P^c_{2,t}$, where $P^{c,e}_{2,t}$ denotes the smoothed probabilities that the developed equity market and the Balkan equity market are jointly in the high (low)-volatility regime.

DATA

We use daily closing prices for the Markov switching regime model and weekly prices for the MS-VAR model, of the following national stock market indices: the Bulgarian Sofix, the Romanian Vanguard, the Turkish ISE National 50, the US S&P500 and the Greek General Index (ASE GI). The data were obtained from national stock exchanges and Bloomberg database. Our sample covers a period of six years, from January 2000 till December 2006. All the above indices are selected to guarantee representativeness of the domestic markets examined in this study. Furthermore, they are expressed in national currencies in order to avoid any currency devaluation in Balkan countries, which may have taken place during this period. Also, when a stock exchange is closed due to a national holiday, we use the previous day closing prices.

EMPIRICAL FINDINGS

Table 1 reports the results of the unit root tests employed in this study. Using eq. (6) to allow for a two regime Markov switching process and eq. (7) to specify the residuals, we observe that there is stationarity according to ADF test in all indices. According to Zivot & Andrews (1992) test, there is also stationarity in the presence of structural break. In all markets, the Markov switching procedure yields a long-run residual series that is stationary without autocorrelation. Thus, the results presented so far provide evidence to support the presence of a regime switching cointegrating relationship.

Table 1
Unit Root Tests

	Augmented Dickey- Fuller		
Country	*Constant*	*Trend*	*Zivot & Andrews*
U.S.	–4.187*	–4.239*	–4.760*
Greece	–5.629*	–5.062*	–6.827*
Turkey	–5.376*	–5.170*	–6.538*
Romania	–6.839*	–6.004*	–5.354*
Bulgaria	–6.421*	–6.279*	–7.302*
Croatia	–6.184*	–6.021*	–7.108*

Note: *denotes significance at the 5% level.

Table 2 presents dynamic coefficient estimates using a Markov two regime error correction model (eq. 8). The lagged Markov residuals have a significantly negative sign in Turkey (–0.268), Romania (–0.58), Bulgaria (–0.08) and Croatia both (–0.327) and (–0.014). In a dynamic context, the estimated long-run relationship shows that the Balkan markets follow the movement of the developed markets. Therefore, allowing for a two regime cointegrating relationship enhances the explanatory power of the long-run equilibrium relationship.

Table 2
Markov Two Switching Regime Error Correction Model

	Log US	*Log Greece*	ECT_{t-1}	*D&W*
Log Turkey	0.483	0.526	–0.268	1.982
	(2.582)*	(2.794)*	(–2.089)*	
Log Romania	0.427	–0.580	0.104	1.979
	(2.084)*	(–2.001)*	(1.973)	
Log Bulgaria	0.318	0.361	–0.008	1.975
	(2.163)*	(2.090)*	(–2.070)*	
Log Croatia	0.306	–0.327	–0.014	1.964
	(1.054)	(–2.026)*	(–2.075)*	

Notes: The error correction model is estimated through eq. 8.
Greece and U.S.A are exogenous variables affecting the Balkan markets.
T-statistics are in parentheses.
Error correction term with 1 lag (t – 1).
D&W denotes the value of the Durbin-Watson test for autocorrelation.
*denotes significance at the 5% level.

Table 3 presents the transition probabilities from one regime to another. The estimates of transition probabilities are statistically significant at the 5% level for all sample markets. In all cases, the results indicate the appearance of two regimes.

Table 3
Markov Switching Regime Characteristics

Transition Matrix		*Regime 1 – Regime 2*	*Probability*
Turkey	Regime 1	0.826 – 0.255	0.608
	Regime 2	0.849 – 0.361	0.642
Romania	Regime 1	0.524 – 0.172	0.470
	Regime 2	0.649 – 0.287	0.522
Bulgaria	Regime 1	0.324 – 0.042	0.686
	Regime 2	0.371 – 0.085	0.579
Croatia	Regime 1	0.286 – 0.048	0.387
	Regime 2	0.294 – 0.042	0.431

So far, we have specified a cointegrating relationship that shifts between two cointegrating regimes. Results provide strong evidence on the dependence between the developed markets and the Balkans markets return regime. Moreover, the regime switching equilibrium appears to be subject to multiple structural breaks.

The main results from estimating the MS-VAR system are reported in Table 4. The first step in our estimation is to determine the lag length l. On the basis of Likelihood Ratio (LR) tests of alternative lengths, a lag length 1 was chosen to estimate model (9). The null hypothesis of no volatility regime is tested against the alternative with volatility regime. We use the LR test and the Davies (1987) bounds. The LR test statistics are 508.36 for Romania, 491.79 for Bulgaria, 494.81 for Turkey and 503.82 for Croatia. This implies that for all four MS-VAR systems the null hypothesis is rejected (implying heteroscedasticity and non-linearity) according to Davies (1987) bounds. Moreover, the Akaike Information Criterion (AIC) supports the MS-VAR model in all cases.

Furthermore, the standard deviation (S.D.) is reported in Table 4. In all cases, Regime 1 is lower than Regime 2, implying that in all four countries Regime 1 can be identified as the "low" volatility regime and Regime 2 as the "high" volatility regime. The transition probability ($p_{1,1}$) that a week of low volatility will be followed by a week of low volatility is 0.72 for the Romanian market, 0.74 for the Bulgarian market, 0.63 for the Turkish market and 0.81 for the Croatian market. On the other hand, the probability that a week of high volatility will be followed by another week of high volatility (i.e. transition probability $p_{2,2}$) is 0.67 for the Romanian market, 0.69 for the Bulgarian market, 0.74 for the Turkish market and 0.69 for the Croatian market. In all cases, except the Turkish market, the low-volatility regime is more persistent than the high volatility regime.

Table 4
MS – VAR model (Balkans vs. Developed Markets)

Parameters	*Romania*	*Bulgaria*	*Turkey*	*Croatia*
LR	508.36	491.79	494.81	503.82
AIC	–8.54	–8.52	–9.07	–8.86
$p_{1,1}$	0.72	0.74	0.63	0.81
$p_{2,2}$	0.67	0.69	0.74	0.69
S.D. of Balkan markets				
Regime 1	0.02	0.02	0.03	0.01
Regime 2	0.04	0.04	0.05	0.02

Notes: The null hypothesis of no volatility regime is tested using eq. (9).
The estimates of the coefficients in eq. (9), not presented here, are available upon request.
Developed markets (Greece and U.S.A) have been entered as exogenous variables in the MS-VAR.
LR denotes the value of the likelihood ratio test for testing the null hypothesis of no volatility regime.
AIC denotes the value of the Akaike Information Criterion.
$p_{1,\,1}$ is the transition probability that a week of low volatility will be followed by a week of low volatility.
$p_{2,2}$ is the transition probability that a week of high volatility will be followed by another week of high volatility.
S.D. stands for the standard deviation.

Then, we test the null hypothesis of independence in volatility regimes between each Balkan stock market and the developed equity markets against the alternative of dependence. The results are reported in Table 5. The Wilcoxon test statistic values range from 11.03 (for the Croatian market) to 14.80 (for the Turkish market). For all four markets, the null hypothesis of independence is rejected. This implies that when the Balkan markets being in high (low) volatility regime is not independent to the fact that the developed markets are also in high (low) volatility regime. Therefore, there is clear evidence of volatility regime linkages between the Balkan and the developed markets.

Table 5
Test for Independence in the Volatility Regime between Balkan and Developed Markets

		Marginal significance level	
Country	*Wilcoxon statistic*	*Bootstrap*	*Asymptotic*
Romania	11.03	0.0000	0.0000
Bulgaria	12.77	0.0000	0.0000
Turkey	14.80	0.0000	0.0000
Croatia	11.68	0.0000	0.0000

CONCLUSIONS

This study investigates a well fitted methodology to model the long-run relationship among four Balkan stock markets, the US and Greece during the period 2000-2006.

The application of an exogenous two switching regime Markov approach shows that structural breaks can model time-varying returns, providing evidence in favour of equity market integration in Balkan stock markets. The model accurately captures typical stock market patterns since it does not rely on linearities.

Equity market integration in Balkan stock market has strong implications on investment decisions and portfolio diversification. Hence, investing in Balkan markets limits the use of portfolio diversification, since the markets tend to move to the same direction with their mature counterparts.

Finally, we identify volatility regime dependence between the Balkan and the developed equity markets. Following a multivariate Markov Switching Vector Autoregression model, we report strong evidence of high and low volatility regime dependence for the Balkan stock markets. This implies that any volatility observed in the developed markets affects the Balkan markets movement.

NOTES

1. See, for example, Richards (1995), Francis and Leachman (1998), Kim *et al.*, (2005) for Europe and the U.S., Arshanapalli and Doukas (1996), Phylaktis (1999) and Manning (2002) for Asian markets, Choudhry (1997) and Chen *et al.*, (2002) for Latin American markets, Jochum *et al.*, (1999), Voronkova (2005), and Syriopoulos (2006) for Central-Eastern European markets.
2. Regime–switching regressions were introduced by Goldfeld and Quandt (1973). Hamilton (1989) extended Markov–switching models to the case of autoregressive dependent data. The vast literature generated by Hamilton (1989) assumes that the regime shifts are exogenous with respect to all realisations of the regression disturbance.
3. The state s_t is a series of consecutive realizations of the actual regime S_t. This allows transforming every K state, $m + 1^{st}$ order Markov chain into an equivalent N state, first order model. If $i, k, \ldots, l$ are past realizations, transition probability $P_{i,j}$ equals Pr $(S_t = i / S_{t-1} = j, S_{t-2} = k, \ldots, S_{t-m} = l)$.
4. Maximum likelihood estimation of equation (9) is based on the Expectation Maximization Algorithm introduced by Hamilton (1989).

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