İşletme Araştırmaları Dergisi
ISSN: 1309-0712
Journal Of Business Research Turk
www.isarder.org

Mutual Switching Behavior between High Growth and Low Growth Economies' Stock Markets

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Abstract

Due to the evolutions in the financial markets, characteristics of markets have been changed. It has become important to discuss the markets which the fast and frequent fluctuations are observed among the regimes they belong to. There are two main purpose of the study. The first purpose of the study is to investigate whether mutual regime switching behavior exists in the selected equity markets. To investigate the importance of growth of the selected economies which the equity markets belong, is the second purpose of the study. Three regime multivariate Markov switching vector autoregressive (MSI(M)-VAR(p)) models are used to define common regime switching behavior of the indices calculated.

Keywords: Regime switching, Markov, Stock Markets, Nonlinearity

1. Introduction

Financial markets, financial decisions and markets' mechanism are not only researched many times but also popular as well. Traditional linear models have problem in forecasting stock prices and returns. Owing to the evolutions in markets, characteristics of markets have changed as well as the stochastic behavior of their return-generating processes.

Behaviors of financial markets' change often abruptly. Not only a part of changes like jumps may be transitory, the changed behaviors of asset prices are continuous in many periods. The mean, volatility, and correlation patterns in stock return's dramatic change by the global financial crisis of 2008-2009 is viewed as an example. Fixed income, equities, foreign exchange markets and the behaviours' of many macro variables have significant relationship with the similar regime changes. Regime switching models try to explain both the sudden changes in behavior and the persistance of the new dynamics in prices (or other fundamentals) in ongoing periods (Ang and Timmermann 2011).

Markov Regime Switching (MRS) models represent the most important example of non-linear time series models. The regime in the models is defined as an unobserved state variable affecting the levels, volatility or correlations of the distributions of stock returns (Perez-Quirors and Timmermann 2000, Guidolin and Timmermann 2008, Chung and Yeh 2008).

MRS models are some of the popular models in financial modeling. The idea of regime changes is natural and intuitive. Also, these models explain fat tails, the periods of turbulence followed by periods of low volatility, skewness, and time-varying correlations in the behavior of many financial series. Moreover, these models can capture nonlinear stylized dynamics of asset returns in a framework based on linear specifications, or conditionally normal or log-normal distributions, within a regime (Ang and Timmermann 2011). Studies created many interesting new questions i.e. it is possible to distinguish distinct regimes in stock market returns, how the regimes differ, how frequent regime switches, when the regime switches occur and if returns and regime switches are predictable are important questions too. The answers to these questions give us new information about stock market returns (Schaller and Norden 1997).

In literature, firstly Hamilton (1989) suggests a model for non-stationary time series, named as Markov switching techniques. The outcomes of a discrete-state Markov process are parameters in this model. Hamilton studied business cycle recessions and expansions. In the study, the regimes naturally explained cycles of economic activity around a long-term trend. These regimes are closely tied to the notion of recession indicators.

The main purpose of the study is to investigate whether mutual regime switching behavior exists in the selected equity markets and whether the heteroskedasticity, skew and fat tails of the stock return distribution could be captured by The Markov switching vector autoregressive (MS(M)-VAR(p)) models with an intercept. Accordingly, MSI(M)-VAR(p) models are used with regime shifts including the intercept in this study.

2. Literature

Finance literature on regime switching models may be driven by observable economic variables called tresholds or may be driven by unobservable stochastic variables as we see in MRS Models. Therewithal there is some literature on testing for the presence of structural breaks in parameters which are unpredictable break-points by using Bayesian Techniques. The MRS models represent the most important example of non-linear time series models. There is a widening literature related in non-linear behavior of the stock markets. Some of these studies are particularly deal with the MRS mechanism. In the early literature, i.e. Schwert (1989) uses a model in which returns may have high or low variance and looks for switches among return distributions determined by a two-state Markov process. In another study, Turner et al. (1989) observe whether mean, the variance or both may differ between two regimes by Markov switching model. Hamilton and Susmel (1994) use several Markov Switching ARCH models which are used to define the volatility of NYSE stock prices. They use models with different number of regimes (i.e. model with 2, 3 and 4).

Analyzing the stock markets with nonlinear models has been taken more interest since 2000. Nielse and Olesen (2000), Seddighi and Nian (2004), Marcucci (2005), Dorina and Simina (2008), Harrison and Moore (2010), Ang and Timmermann (2011), Balcılar et al. (2015), Song et al. (2016) are some of the recent studies. Nielsen and Olesen (2000) estimate a well-specified two-state regime-switching model for Danish stock returns by using low return-low volatility and high return-high volatility. Two regimes are identified in the model and it is observed that the indication of mean reversion is due to the recent high return-high volatility regime only. Ang and Timmermann (2011) discuss regime changes models, their effect on equilibrium asset prices in their study and try to find empirical evidence consistent with regimes in a variety of asset return series in equities, fixed income and currency markets. An equilibrium model is offered in which regimes are in fundamental processes, like consumption or dividend growth, significantly affect the dynamic properties of equilibrium asset prices. Also this equilibrium model can induce non-linear risk-return trade-offs. Finally regime switches affect investors' optimal portfolio choice.

Çevik, Korkmaz and Atukeren (2012) analyze US all shares stock returns corresponding to the New York Stock Exchange (NYSE). Following using MRS models to investigate the nonlinear structure of stock returns, the role of business confidence in manufacturing and nonmanufacturing sectors in explaining stock market regimes and regime switches are studied.

Based on the good explanation power of MRS models, the relationship between other variables and stock returns are analyzed in literature. Kim, Kim and Choi (2017) studies the effects of interest rates and foreign exchange rates in a two regimed model for the stock indices KOSPI, NIKKEI225, Dow Jones and Shanghai B. In another study Zhu, Su, You and Ren (2016) analyze the effects of oil price shocks on stock returns for oil-importing and oil-exporting countries. It is found in the study that structural oil shocks have statistically significant impacts on stock returns when switching is allowed.

3.Data and Methodology

3.1.Data

The assumption of the study is that the indices of selected emerging countries settled in the global financial portals such as finance.yahoo.com, investing.com, Bloomberg.com and BBC Business followed by the international investors. These indices are BIST100 (TURKEY), BOVESPA (Brazil), DOHA (Qatar), IDX COMPOSITE (Indonesia), IPC (Mexico), IPSA (Chile), KOSPI (South Korea), MICEX (Russia), NIFTY50 (India), South Africa 40 (South Africa) and WIG20 (Poland).

In literature, there are some evidence that economic growth have a relationship with the equity market. Some of the literature indicate that they have positive relationship (Rousseau and Wachtel (2000), Beck and Levine (2004), Ngare et all (2014), Kaplan(2008)) and others not (Arestis et all (2001), Naceur and Ghazouani (2007)). Particularly, determination of this relationship might be necessary in the emerging markets because of the lack of leading indicators (Gozbasi: 2015). Unlike the literature, we used the economic growth to form two different indices. The growth of the economies differentiate the selection of the sample. We formed an index which is computed from the equity market indices of the high economic growth emerging markets and the other emerging markets' economies have low growth. Table 1 shows the first five high growth economies in the five years periods.

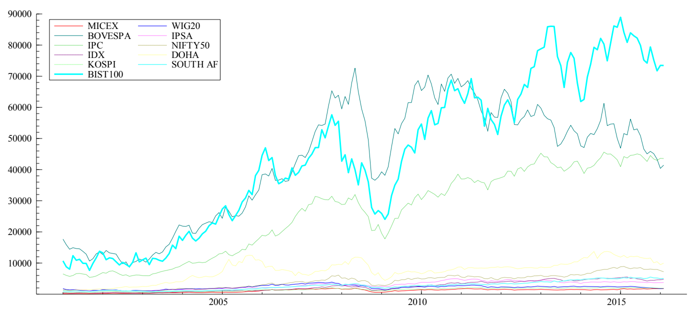
Table 1: High Growth Countries

1990-1994	China	South Korea	Chili	Luxemburg	Ireland
1994-1999	China	Ireland	Poland	Chili	Estonia
2000-2004	China	Russia	Estonia	Latvia	Ireland
2005-2009	China	Russia	Slovakia	Turkey	Saudi Arabia
2010-2014	China	Chili	Turkey	Saudi Arabia	Russia

Monthly data of 2001:01-2016:2 which includes 182 observations have been used in the study. The indices are divided into two groups as an index of the high growth countries in the first five in any five years period or index of the low growth countries that could not found in the first five. The high growth economies in the five years periods are calculated from the data of the OECD. Developing countries Chile, Turkey and Russia with economic growth rates that will be leading economies were included in the calculation index HG. Also Poland and South Korea with high growth rates by 5-year period between 1990-2014 period were also included to enlarge the sample. The index of the high growth economies consists of BIST100 (TURKEY), IPSA (Chile), KOSPI (South Korea), MICEX (Russia) and WIG20 (Poland). The index of the low growth economies is composite of BOVESPA (Brazil), DOHA (Qatar), IDX COMPOSITE (Indonesia), IPC (Mexico) and NIFTY50 (India). The number of the trading days differs in markets due to the holidays. Therefore using monthly data is appropriate to analyze.

The new indices named as Index HG (BIST100, IPSA, KOSPI, MICEX and WIG20) and Index LG (BOVESPA, DOHA, IDX COMPOSITE, IPC and NIFTY50) formed by arithmetic means of the groups. The market indices are shown in Figure 1 and the indices that formed by us are shown in Figure 2. We use the logarithmic differences of two new indices which may be seen in Figure 3.

Figure 1: Market Indices



Index HG: Chile (IPSA), Poland (WIG20), Russia (MICEX), South Corea (KOSPI), Turkey (BIST100).

Index LG: Brazil (BOVESPA), India (NIFTY50), Indonesia (IDX COMPOSITE), Mexico (IPC), Qatar (DOHA), South Africa (South Africa 40).

Figure 2: Index High Growth and Index Low Growth

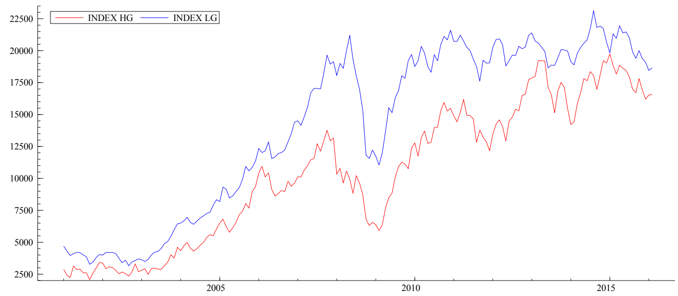
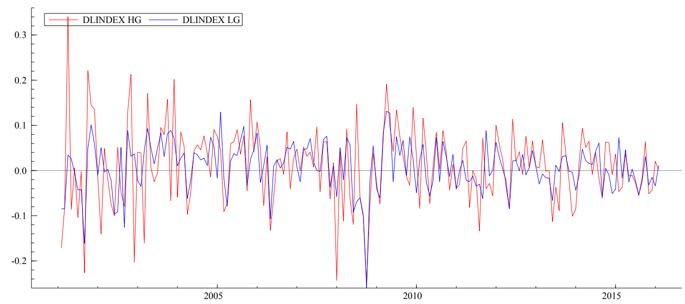


Figure 3: Logarithmic Differences of High and Low Growth Indices



3.2. Methodology and Model: The Markov Switching Vector Autoregressive Model

A markov chain is composed of independent random variables. The basic idea for the MRS Model is to describe a situation or stochastic process that determines the change from the regime to the other via a Markov chain. Markov chain is used to model the behavior of a state variable or combination of variables which cannot be directly observed but determines the regime. In a MRS the state of the economy (s_t) cannot be directly observed, although the time series variable (v_t) can be observed. Any period of economy whose properties depend on the observation values, is obtained as probability. At the same time those observations are supposed to be dependent on the properties of the regime. When the state of the economy in the Markov regime is determined, the next regime can be expressed as a probability (Bildirici et all 2000).

The idea behind 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 which represents the probability of being in a particular state of the world (Krolzig 2000).

p(yt|Yt−1;Xt; st: (1)

f(yt|Yt−1;Xt; ϴ1) if st = 1

f(yt|Yt−1; Xt; ϴM) if st = M

Xt: exogenous variables; ϴ is the parameter vector associated with regime M.

In Markov Switching models the regime-generating process is an ergodic Markov chain with a finite number of states defined by the transition probabilities (Krolzig 2000).

$p_{ij} = \Pr(s_{t+1} = j | s_t = i); \sum_{j=1}^{M} P_{ij}=1$; i,j ={1,..,M} (2)

s_t follows an ergodic M-state Markov process with an irreducible transition matrix:

$$\mathbf{P} = \begin{vmatrix} p_{11} & \cdots & p_{1M} \\ \cdots & \cdots & \cdots \\ p_{M1} & \cdots & p_{MM} \end{vmatrix} \quad (3)$$

The probability which regime is in operation at time t conditional on the information at time $t-1$ only depends on the statistical inference on s_{t-1}:

$\Pr(s_t | Y_{t-1}; X_t; S_{t-1}) = \Pr(s_t | s_{t-1})$ (4)

Markov Switching time series analysis is firstly implemented by Hamilton (1989) in the business cycle. Hamilton reexamined the possibility that macroeconomic variables evolve on a cyclical time scale. The relationship between economic and calendar time in turn depends on the economic history of the process, such as whether the economy has been in a cyclical expansion or contraction.

The main different kinds of the model are MSM and MSI models. In MSM Model, the regime switches according to the conditional mean (μ_t), on the other hand in MSI Model, the regime switches according to the constant (c_{st}).

MSM Model: $y_t - \mu_t = \phi(y_{t-1} - \mu_{t-1}) + u_t$ (5)

MSI Model: $y_t - c_{st} = \phi y_{t-1} + u_t$ (6)

MSIH Model: $y_t - c_{st} = \phi y_{t-1} + u_t + \Omega^{1/2}$ (7)

ϕ is an n x n matrix of regime-dependent autoregressive coefficients

u_t is an (n*1) unobservable zero mean white noise vector process

Matrix $\Omega^{1/2}$ represents the factor applicable to state s_t in a state-dependent Choleski factorization of the variance covariance matrix of variable (y) $\Omega\ s_t$.

$\Omega\ s_t = Var[y_t | \varkappa_{t-1}, s_t]$; (8)

$\varkappa_{t-1}$: denotes time t-1 information of all past observations and states.

A linear vector autoregression (VAR) model is a natural extension of the univariate autoregressive model to dynamic multivariate time series. A Markov switching vector autoregressive model allows asymmetric (regime dependent) inference for causality (Balcılar and Ozdemir, 2013).

The basic p lagged VAR(p) model process is:

$y_t = c + [A_1 y_{t-1} + \ldots + A_p y_{t-p}] + u_t$; (9)

A_n is (n*n) coefficient matrices

The general form of a Markov-switching vector autoregressive (MS-VAR) process is (Krolzig 1998, 2000):

$y_t = c(s_t) + [A_1(s_t) y_{t-1} + \ldots + A_p(s_t) y_{t-p}] + u_t$ (10)

A VAR with regime shifts in the *mean* is called a MSM(*M*)-VAR(*p*) process:

$$y_t = \mu(s_t) + A_1(s_t)(y_{t-1} - \mu(s_{t-1})) + \ldots + A_p(s_t)(y_{t-p} - \mu(s_{t-p})) + u_t \tag{11}$$

$u_t \sim NID(0, \Sigma(s_t))$

If the regime shifts affect the *intercept* of the VAR, this is called a MSI(*M*)-VAR(*p*) process:

$$y_t = c(s_t) + A_1(s_t)y_{t-1} + \ldots + A_p(s_t)y_{t-p} + u_t \tag{12}$$

After a shift in regime, the transition to the new (conditional) mean is smooth in an MSI-VAR and once-and-for-all in an MSM-VAR. MSM-VAR and MSI-VAR processes represent the subclass of MS-VAR processes for which optimal predictor can be derived analytically and computationally effective algorithms can be constructed easily (Krolzig 1998, 2000).

If the regime shifts affect the intercept of the VAR and the model includes a variance covariance matrix, this is called a MSIH(*M*)-VAR(*p*) process:

$$y_t = c(s_t) + A_1(s_t)y_{t-1} + \ldots + A_p(s_t)y_{t-p} + u_{t\,+}\,\Omega^{1/2} \tag{13}$$

MSIH(*M*)-VAR(*p*) model means “Markov switching”, “Intercept regime dependent”, “Vector autoregressive”, “heteroskedastic” model (Guidolin 2006).

It is possible to analyze in MS-VAR models how other variables are affected if shocks applied to a variable. Impulse response functions of the models show these relations in different regimes. For example, if the model includes two variables and has got three regimes, there should be six (2*3=6) relations to analyze.

4. Results

2 and 3 regime switching models are applied with different lags to the logarithmic differences of Index High Growth and Index Low Growth. We select the models with a Davies’ criteria smaller than 0.05 which reject the Davies criteria’s null hypothesis of linearity. The information criterions of the models are shown in Table 2, 3,4, 5 and 6.

MS(p)-VAR(1) models are shown in Table 2. According to the information criterions, MSIAH(3)-VAR(1), MSIA(3)-VAR(1) and MSIH(3)-VAR(1) models are successful in examining the relationships.

All of the three models have three regimes. The first regime is recession, the second regime is moderate growth and the third regime is expansion. Besides, each of the models has got an intercept. We look to LR linearity criterion to see how much the non-linear model explains the relation more than the linear model. Of the three models, MSIAH(3)-VAR(1) is the most powerful one.

Table 2: The Information Criterions of The Models with 1 Lag

Model	log-likelihood	AIC	HQ	SIC	LR Linearity	DAVIES
MSI(2)-VAR(1)	508.7168	-5.5080	-5.4145	-5.2774	12.4398	0.0267
MSI(3)-VAR(1)	521.2291	-5.5803	-5.4437	-5.2443	37.4643	0.0000
MSIH(2)-VAR(1)	515.2425	-5.5471	-5.4321	-5.2633	25.4911	0.0027
MSIH(3)-VAR(1)	**529.8545**	**-5.6095**	**-5.4297**	**-5.1660**	**54.7152**	**0.0000**
MSIA(2)-VAR(1)	513.5625	-5.5174	-5.3951	-5.2158	22.1312	0.0223
MSIA(3)-VAR(1)	**533.4325**	**-5.6270**	**-5.4328**	**-5.1481**	**61.8712**	**0.0000**
MSIAH(2)-VAR(1)	521.1572	-5.5684	-5.4246	-5.2136	37.3205	0.0007
MSIAH(3)-VAR(1)	**542.6427**	**-5.6627**	**-5.4254**	**-5.0773**	**80.2914**	**0.0000**
MSM(2)-VAR(1)	509.5899	-5.5177	-5.4242	-5.2871	14.1859	0.0126
MSM(3)-VAR(1)	518.5688	-5.5508	-5.4141	-5.2137	32.1436	0.0001
MSMH(2)-VAR(1)	518.0824	-5.7055	-5.5886	-5.4173	37.7581	0.0000
MSMH(3)-VAR(1)	523.7047	-5.6671	-5.4844	-5.2167	49.0027	0.0000

MS(p)-VAR(2) models are shown in Table 3. According to the information criterions, MSIAH(3)-VAR(2), MSIA(3)-VAR(2) and MSIH(3)-VAR(2) models are more successful than others. Besides, each of these three models is more successful than the same kind of model with one lag.

Table 3: The Information Criterions of The Models with 2 Lag

Model	log-likelihood	AIC	HQ	SIC	LR Linearity	DAVIES
MSI(3)-VAR(2)	522.4891	-5.5809	-5.4148	-5.1713	42.6193	0.0000
MSIH(2)-VAR(2)	523.1376	-5.6216	-5.4772	-5.2655	43.9164	0.0000
MSIH(3)-VAR(2)	**529.3336**	**-5.5903**	**-5.3809**	**-5.0739**	**56.3084**	**0.0000**
MSIA(2)-VAR(2)	520.1440	-5.5323	-5.3518	-5.0872	37.9292	0.0012
MSIA(3)-VAR(2)	**541.8393**	**-5.6183**	**-5.3367**	**-4.9239**	**81.3898**	**0.0000**
MSIAH(2)-VAR(2)	527.6837	-5.5831	-5.3809	-5.0845	53.0085	0.0000
MSIAH(3)-VAR(2)	**558.7313**	**-5.7400**	**-5.4151**	**-4.9387**	**115.1038**	**0.0000**
MSM(3)-VAR(2)	519.2245	-5.5444	-5.3783	-5.1349	36.0902	0.0000
MSMH(2)-VAR(2)	519.1486	-5.6721	-5.5260	-5.3119	38.0936	0.0000
MSMH(3)-VAR(2)	525.4634	-5.6416	-5.4297	-5.1192	50.7230	0.0000

MS(p)-VAR(3) models are shown in Table 4. The most powerful three models are MSIAH(3)-VAR(3), MSIA(3)-VAR(3) and MSIAH(2)-VAR(3).

Table 4: The Information Criterions of The Models with 3 Lag

Model	log-likelihood	AIC	HQ	SIC	LR Linearity	DAVIES
MSI(3)-VAR(3)	523.1960	-5.5752	-5.3795	-5.0926	27.1251	0.0005
MSIH(2)-VAR(3)	527.5158	-5.6575	-5.4835	-5.2285	35.7645	0.0000
MSIH(3)-VAR(3)	**532.6671**	**-5.6142**	**-5.3750**	**-5.0244**	**46.0671**	**0.0001**
MSIA(2)-VAR(3)	**540.1363**	**-5.6982**	**-5.4589**	**-5.1083**	**61.0056**	**0.0000**
MSIA(3)-VAR(3)	**551.8751**	**-5.6278**	**-5.2581**	**-4.7162**	**84.4832**	**0.0000**
MSIAH(2)-VAR(3)	**545.7651**	**-5.7277**	**-5.4667**	**-5.0842**	**72.2632**	**0.0000**
MSIAH(3)-VAR(3)	**564.6898**	**-5.7044**	**-5.2912**	**-4.6855**	**110.1126**	**0.0000**
MSM(3)-VAR(3)	520.8555	-5.5489	-5.3532	-5.0663	22.4380	0.0035
MSMH(2)-VAR(3)	521.5481	-5.6540	-5.4786	-5.2216	38.8869	0.0000
MSMH(3)-VAR(3)	526.6752	-5.6099	-5.3688	-5.0154	49.1356	0.0000

MS(p)-VAR(4) models are shown in Table 5. MSIAH(3)-VAR(4), MSIA(3)-VAR(4) and MSIA(2)-VAR(4) models are the most powerful models of the four autoregressive lagged models. Besides, MSIH(3)-VAR(4) model is more successful than the 2 and 3 lagged MSIH(3)-VAR(q) models.

Table 5: The Information Criterions of The Models with 4 Lag

Model	log-likelihood	AIC	HQ	SIC	LR Linearity	DAVIES
MSI(2)-VAR(4)	515.1621	-5.5386	-5.3566	-5.0899	16.4716	0.0046
MSI(3)-VAR(4)	524.0250	-5.5709	-5.3453	-5.0146	34.1974	0.0000
MSIH(2)-VAR(4)	527.3496	-5.6424	-5.4386	-5.1399	40.8466	0.0000
MSIH(3)-VAR(4)	**536.0216**	**-5.6387**	**-5.3694**	**-4.9747**	**58.1906**	**0.0000**
MSIA(2)-VAR(4)	**544.1364**	**-5.6852**	**-5.3868**	**-4.9494**	**74.4202**	**0.0000**
MSIA(3)-VAR(4)	**568.4708**	**-5.7115**	**-5.2531**	**-4.5810**	**123.0890**	**0.0000**
MSIAH(2)-VAR(4)	**543.7013**	**-5.6463**	**-5.3261**	**-4.8568**	**73.5499**	**0.0000**
MSIAH(3)-VAR(4)	**584.2131**	**-5.8216**	**-5.3195**	**-4.5835**	**154.5736**	**0.0000**
MSM(2)-VAR(4)	512.9587	-5.5136	-5.3317	-5.0650	12.0629	0.0314
MSM(3)-VAR(4)	519.2287	-5.5167	-5.2911	-4.9604	24.6048	0.0014
MSMH(2)-VAR(4)	524.6460	-5.6437	-5.4391	-5.1393	43.1582	0.0000
MSMH(3)-VAR(4)	532.0003	-5.6250	-5.3547	-4.9585	57.8666	0.0000

MS(p)-VAR(5) models are shown in Table 6. MSIAH(3)-VAR(5), MSIA(3)-VAR(5) and MSIA(2)-VAR(5) models are the most three powerful models in the table. By the 5th lag, the LR linearity criteria of the models begin to decline.

Table 6: The Information Criterions of The Models with 5 Lag

Model	log-likelihood	AIC	HQ	SIC	LR Linearity	DAVIES
MSI(2)-VAR(5)	513.8137	-5.5092	-5.2974	-4.9868	16.1521	0.0053
MSI(3)-VAR(5)	521.9946	-5.5340	-5.2783	-4.9035	32.5139	0.0000
MSIH(2)-VAR(5)	525.8205	-5.6116	-5.3778	-5.0351	40.1655	0.0000
MSIH(3)-VAR(5)	**534.5886**	**-5.6090**	**-5.3094**	**-4.8704**	**57.7019**	**0.0000**
MSIA(2)-VAR(5)	**547.3859**	**-5.6635**	**-5.3055**	**-4.7808**	**83.2959**	**0.0000**
MSIA(3)-VAR(5)	**580.7317**	**-5.7470**	**-5.1990**	**-4.3959**	**149.9880**	**0.0000**
MSIAH(2)-VAR(5)	**548.2734**	**-5.6395**	**-5.2595**	**-4.7027**	**85.0714**	**0.0000**
MSIAH(3)-VAR(5)	**581.0568**	**-5.6825**	**-5.0906**	**-4.2233**	**150.6382**	**0.0000**
MSM(2)-VAR(5)	513.4372	-5.5050	-5.2931	-4.9826	15.3990	0.0074
MSM(3)-VAR(5)	519.6045	-5.5069	-5.2511	-4.8764	27.7336	0.0004
MSMH(2)-VAR(5)	525.9669	-5.6133	-5.3795	-5.0368	40.4584	0.0000
MSMH(3)-VAR(5)	534.9489	-5.6131	-5.3135	-4.8745	58.4224	0.0000

If Table 2,3,4,5 and 6 are summarized, first the most powerful kind of MS-VAR models are MSIAH, MSIH and MSAH for our variables. Second, models with four lag are more successful than other models. The impulse response function of MS-VAR models doesn’t work with MSIAH-VAR and MSAH-VAR models. Because of this reason we choose the most powerful MSIH-VAR model and analyze it.

The coefficients of the selected model are shown on the Table 7.

In the regime 1 (recession) and regime 2 (moderate growth) the constants of the dependent variables are very close to each other (Index LG (-0.0936, 0.0104); Index HG (-0.0909, 0.0141)). With reference to the constants, we may expect a similar movement from two indices in the recession regime and moderate growth regime. In the regime 3 (expansion), the constant of the model which describes Index LG (0.0413) is bigger than the constant of the model which describes Index HG (0.0285). In the expansion regime, we may watch a stronger movement from the Index LG. As given on table, the relationship between Index HG and it’s lags is both negative (-0.1147, -0.0572, -0.1766, -0.2127). However, the relations between Index HG and the lags of the Index LG are mostly positive (0.2337, -0.0102, 0.2615, 0.3598).

While examining the relationship between Index LG and it’s lags, it is observed that the coefficients of the first and second lags are negative. However, the coefficients of the third and fourth lags are positive. Conversely in the same model, the coefficients of the first and second lags of Index HG are positive although the coefficients of the third and fourth lags are negative.

Table 7: Coefficients

	INDEX HIGH GROWTH	INDEX LOW GROWTH
Constant (Regime 1)	-0.0909	-0.0936
Constant (Regime 2)	0.0141	0.0104
Constant (Regime 3)	0.0285	0.0413
INDEX HIGH GROWTH -1	-0.1147	0.1040
INDEX HIGH GROWTH -2	-0.0572	0.0694
INDEX HIGH GROWTH -3	-0.1766	-0.0789
INDEX HIGH GROWTH -4	-0.2127	-0.1127
INDEX LOW GROWTH -1	0.2337	-0.0678
INDEX LOW GROWTH -2	-0.0102	-0.1297
INDEX LOW GROWTH -3	0.2615	0.1203
INDEX LOW GROWTH -4	0.3598	0.2325
Standard Error (Regime 1)	0.1153	0.0669
Standard Error (Regime 2)	0.0594	0.0430
Standard Error (Regime 3)	0.1135	0.0343

Table 4 shows the probabilities of regime transitions. If equity markets in any day are known as they are in regime 1; the following day the markets are expected to be 61.27% in regime 1, 08.61% in regime 2 and 30.12% in regime 3. For instance if the indices' returns are negative in any day, the returns are expected to be 61.27% negative at the end of the following day. If the markets are known as they are in regime 2; the following observation is expected to be 98.65% in regime 2, 01.22% in regime 1 and 00.12% in regime 3. If the market is known as it is in regime 3; the following observation is expected to be 83.91% in regime 3, 11.34% in regime 1 and 04.75% in regime 2. If the markets' volatilities are high and the returns are positive in any day, the next day's returns are expected to be 83.91% positive. The international investors might do their portfolio selection due to this information.

Table 4: Transition Probabilities

	Regime 1	Regime 2	Regime 3
Regime 1	0.6127	0.0861	0.3012
Regime 2	0.0122	0.9865	0.0012
Regime 3	0.1134	0.0475	0.8391

In the observation period, regime 2 has the maximum number of observation (135) the highest probability (81.76) and the highest duration (74.12). If market is in moderate growth, expected duration is 74 month. The minimum number of observation (13), the minimum probability (0.0613) and the minimum duration belongs to regime 1. The durations of recession regime (2.58) and expansion regime (6.22) are very short while compared with the moderate growth regime (74.12).

Table 5: Regime Probabilities

	Number of Observations	Probability	Duration
Regime 1	13	0.0613	2.58
Regime 2	135	0.8176	74.12
Regime 3	28	0.1211	6.22

The contemporaneous correlations of the indices are shown in the next tables. This type of correlation shows the correlation between two time series in the same regime. The highest correlation is found in the moderate growth regime, although the lowest correlation is found in the expansion regime.

Table 6: Contemporaneous Correlation –Regime 1

	INDEX HIGH GROWTH	INDEX LOW GROWTH
INDEX HIGH GROWTH	1	0.5305
INDEX LOW GROWTH	0.5305	1

Table 7: Contemporaneous Correlation –Regime 2

	INDEX HIGH GROWTH	INDEX LOW GROWTH
INDEX HIGH GROWTH	1	0.5781
INDEX LOW GROWTH	0.5781	1

Table 8: Contemporaneous Correlation –Regime 3

	INDEX HIGH GROWTH	INDEX LOW GROWTH
INDEX HIGH GROWTH	1	0.4771
INDEX LOW GROWTH	0.4771	1

The probabilities of the regimes are shown in the next figure. The longest observation belongs to regime 2 (more than 7 years) called as moderate growth.

Figure 4: Regime Probabilities

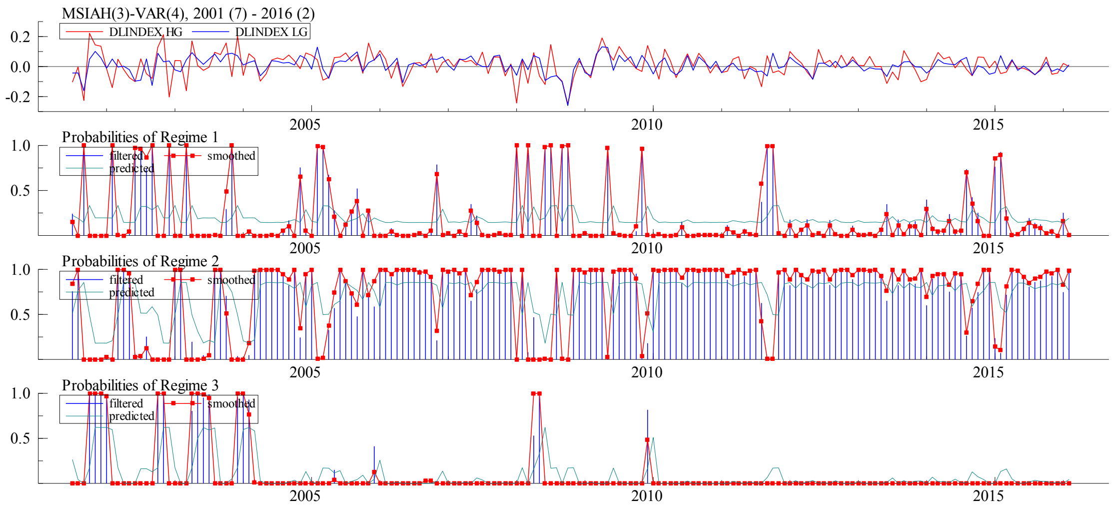


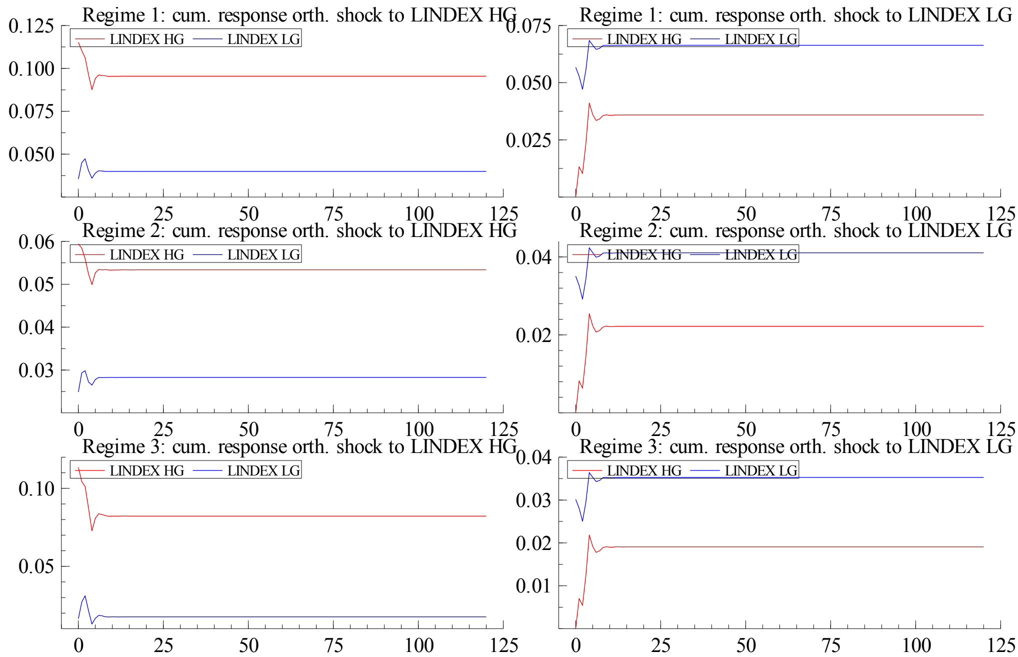
Table 9 shows the details of the cycle dates. The recession regime of the model captures the September 11 attacks which were a series of four coordinated terrorist attacks by the Islamic terrorist group Al-Qaeda. After the second plane crashed into the World Trade Center, the trading in New York Stock Exchange (NYSE) and NASDAQ were cancelled. London Stock Exchange and some other stock exchanges around the world were closed too. Besides, the model captures the 2008 Global Crisis which is the last important stock market crash.

Table 9: Cycle Dates

Regime 1 : Recession	Regime 2: Moderate Growth	Regime 3: Expansion
2001:8 - 2001:9 [0.7463] 2002:5 - 2002:9 [0.8555] 2008:1 - 2008:1 [0.9819] 2008:6 - 2008:10 [0.9994]	2004:2 - 2007:12 [0.9865] 2008:11 - 2016:2 [0.9940]	2001:7 - 2001:7 [0.3768] 2001:10 - 2002:4 [0.9560] 2002:10 - 2004:1 [0.9522] 2008:2 - 2008:5 [0.9673]

The results of the impulse-response functions of the MSIH(3)-VAR(3) model are shown in Figure 5. The first line is regime 1, the second line is regime 2 and the last line is regime 3. In the first column the shock is applied to Index High Growth and in the second column to Index Low Growth.

Figure 5: Impulse Response Tests



If one standard deviation’s shock is applied to Index HG;

Regime 1: Index LG rises in the first month nearly 0.05, then falls to nearly 0.03 and lasts by 0.03. The biggest response is in the recession regime.

Regime 2: Index LG rises in the first month nearly 0.03, then falls to nearly 0.028 and lasts by 0.028.

Regime 3: Index LG rises in the first month nearly 0.025, falls to nearly 0.01 and lasts by 0.01. The minimum lasting effect is in the expansion regime.

If one standard deviation’s shock is applied to Index LG;

Regime 1: Index HG rises in the first month nearly 0.04, falls to nearly 0.035 and lasts by 0.035. The biggest response and the maximum lasting effect is in the recession regime.

Regime 2: Index HG rises in the first month nearly 0.026, falls to nearly 0.023 and lasts by it.

Regime 3: Index HG rises in the first month nearly 0.021, falls to nearly 0.020 and lasts by it. The minimum lasting effect is in the expansion regime.

5. Conclusion

In this study, we have investigated two main subjects. The main purpose of the study is to investigate whether a mutual regime switching behavior exists in the selected equity markets. The other purpose is to investigate the importance of growth of the selected economies which the equity markets belong.

The MRS models which represent the most important example of non-linear time series models of current application are used in the study. The financial markets are observed with fast and frequent fluctuations which are also might seen as the recession and expansion regimes. MRS models successfully capture the regimes in the financial markets. We find many kinds of MRS models explaining the relationship. The model MSIH(M)-VAR(p) is the best describing model. Model with "Markov switching", "Intercept regime dependent", "heteroskedastic", "Vector autoregressive" characteristics is used to analyze 2001:01-2016:2 period. MSIH(3)-VAR(4) model by minimum Schwarz Criteria and maximum LR Linearity have three regimes and four autoregressive lags. The first regime in the model is recession, the second is moderate growth and the third is expansion. The variance distinguishes moderate growth and expansion regime from each other. When the variance and/or volatility of regime moderate growth is relatively low, it is high in the expansion regime.

It is observed that the coefficients of both index HG and the index LG in recession and moderate growth regime is very close together. Only the coefficient of index LG in regime expansion is relatively high to index HG. The high probability of staying in the same regime by transition possibilities supports the model as correctly identified. It is noteworthy by regime probabilities that duration is high in the second regime – moderate growth. This model shows the market's possibility of staying longest in average (74 months) that is moderate growth regime in which volatility is lower than others. It is an evidence that the investors take a long-term investment decisions in low volatile and moderate growing markets. The highest correlation between the indices belongs to moderate growth regime.

The impulse response analysis shows that a standard deviation shock applied to one of the index for all regimes caused a positive response on the other indices in the first month. As direction of the reaction is same, the size and persistence varies according to regime and indices. Another important result is that the model captures the global crisis 2008 and September 11 attacks by cycle date.

The probabilities and durations of the regime switching mechanism of this model are important for international investors in selecting portfolios. The investors may select the stocks according to the duration and probabilities of the regimes. For instance if the market is high volatile and returns are positive, they should expect this returns for maximum 6 months. After nearly six months the regime should change. First, in any day the investors might examine the returns, volatility, and suppose which regime the information shows. Second they should decide the portfolio selection by using the probabilities and durations.

The study presents evidence for variables affecting emerging stock markets on the integration process with international markets and existence of unobservable state variables in these markets. It is indicated that the low or high growth speed of the economies emerging markets does not change the response of these markets to the new information. The regimes created by the fluctuations in financial markets lead the international markets to move in the same direction.

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