Volatility spillover across energy indices of the stock markets

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ABSTRACT

The paper will use a MSGARCH model to analyze how are transmitted the sudden changes in volatility transmission from the energy market across several energy indices including Romania. In addition to the GARCH models, the class of Markov-switching GARCH (MSGARCH) may provide an early warning indication of changes in the conditional volatility. We use daily closing data spanning a ten year period in order to capture the dependencies and sensitivities of energy related equity sector.

Keywords: *energy market, stock market indices, Markov Switching*

LITERATURE REVIEW

Single regime GARCH models namely the GARCH models in which the conditional variance is modeled as being in only one regime, are prone to misread the data when there are occurring sudden shocks in the market. Strong shocks have the ability to move the market in a higher volatility regime which is characterized by a higher conditional variance and is due to the market uncertainties. Therefore the standard GARCH model may not be able to quickly react and, most important, to indicate when a transition is happening.

Another critique of the GARCH models comes from the fact that has usually a low power in their out-of-sample forecasts. In this respect Hamilton and Susmel (1994) showed that using a forecast from standard GARCH (1, 1) model is less than the sample variance. In these circumstances Hamilton and Susmel, Cai (1994) suggested a Markov switching ARCH (also known as SWARCH) as a better model as opposed to a standard GARCH.

MS-GARCH are difficult to estimate since the variance is autoregressive and path-dependent it will depends on all the preceding unobserved state variables, because a Markov model assumes a hidden state variable that allows the switches between the regime.

The SWARCH model of Hamilton and Susmel (1994) is in this respect easier to solve since the ARCH effects do not have this path dependency issue.

MS-GARCH are nonlinear models in which endogenous risk is modeled such as the behavior of market players creates additional risk with respect to the uncertainty of fundamental news.

Gray (1996) introduced a Markov Switching GARCH and applied to United State's Treasury Bill and Edwards and Susmel (2003) used a SWARCH model to study volatility of interest rates. Wang and Theobald (2008) used a Markov Switching model to find out which is the impact of financial liberalization on return volatility using data from six Asian emerging stock markets. In order to quantify the impact of oil price on the economic growth of G7 countries, Cologni and Manera (2009) used a switching regime approach. Their results indicated that the oil prices shocks are declining on the business cycles of G7 countries.

An MS-GARCH model allows investigating if there is any change in the variance of the indices returns. Given the importance of the energy markets, we believe that using a non-linear approach, namely a MS-GARCH model, may provide a deeper understanding of the market participants behavior.

MODEL

In literature have been proposed few methods for computing the likelihood function. We will present Dueker approach (1997) since it seems more practical. Our model is a conditionally Gaussian model with asymmetry two-regime, one lag, using the Hamilton-Susmel inflation factors.

By using a regime switching approach, the time series is divided in different phases (state/ regime) and each phase has specified its own underlying stochastic process. We consider the Markov regime switching model in which the state variable is a latent, unobservable variable denoted by S_t.

We limit in this paper to a MS-GARCH model with two states, so that the state space is S = {1, 2}.

We assume a Gaussian distribution for errors.

$$y_t = \mu_t + \epsilon_t \ , \epsilon_t \sim N\left(0, \sigma^2\right)$$

The conditional mean switches between states according to a Markov process which is driven by a state variable (S_t). The hidden state variable follows a first order Markov Chain with constant transition probabilities given by

$$Prob\ (S_t = 0 | S_{t-1} = 0) = p$$
$$Prob\ (S_t = 1 | S_{t-1} = 1) = q$$
$$Prob\ (S_t = 0 | S_{t-1} = 1) = 1 - q$$
$$Prob\ (S_t = 1 | S_{t-1} = 0) = 1 - p$$

In matrix notation[1]

$$P = \begin{bmatrix} p & 1-q \\ 1-p & q \end{bmatrix}$$

1 R code snippets:construct probabilities
```
p_s0_s0 <- pnorm(gamma_s0)
p_s0_s1 <- pnorm(gamma_s1)
p_s1_s0 <- 1-pnorm(gamma_s0)
p_s1_s1 <- 1-pnorm(gamma_s1)
```

The equation for the conditional mean is:

$$\mu_t = \mu_l S_t + \mu_h(1 - S_t), S_t \in \{0,1\}$$

where μ_l is the mean in the low volatility regime and μ_h is the mean for the high volatility regime.

The unconditional probability of S_t being zero is equal with (1-q)/(2-p-q)[1]. The variance of errors is σ_t^2 and is assumed to be Garch(1,1) process with Markv-Switching dynamics driven by a state variable (S_t). The equation for the variance is

$$h_t(S_t, S_{t-1}, \dots S_0) = \gamma(S_t) + \alpha(S_{t-1})\epsilon_{t-1}^2 + \beta(S_{t-1})h_{t-1}(S_{t-1}, \dots S_0)$$

The variance of errors still depends on the entire history of the state variable. In the SWARCH model of Cai (1994) the variance is depending only on the most recent values of the state variable.

Due to computational issues involved in the calculation of the likelihood function when the time series is big, for example a four year time series with daily frequency, Kim (1994) suggested a simplifying procedure for evaluating the likelihood function[2]. This procedure sees the conditional variance as a function of the most recent M values of the state variable, so that the conditional variance is rewritten as a function of only S_t and S_{t-1}.

$$h_t^{(i,j)} = h_t(S_t = i, S_{t-1} = j)$$

Therefore the procedure of collapsing $h^{(i,j)}$ on $h^{(i)}$ gives a formula for the variance in which the first lag of the state variable S_{t-1} is marginalized out.

$$h_t^{(i,j)} = \gamma(S_t = i) + \alpha(S_{t-1} = j)\left(\epsilon_{t-1}^j\right)^2 + \beta(S_{t-1} = j)h^j{}_{t-1}$$

Since GARCH processes are functions of the lagged values of the state variable, the conditional variance is modeled as a function of only S_{t-1} and so the equation for the variance may be written as

$$h_t^j = \gamma + \alpha(S_{t-1} = j)\left(\epsilon_{t-1}^j\right)^2 + \beta(S_{t-1} = j)\hat{h}_{t-1}$$

Since there are several specification of the MSGARCH model, in the following we are fitting a model similar with the SWARCH model of Hamilton and Susmel (1994) which make use of normalization factor (g) so that the conditional variance is written as

$$\sigma_t^2 = g_t h_t$$

1 R code snippets: use unconditional probabilities
p0_s0 <- (1 - p_s1_s1) / (2 -p_s0_s0 -p_s1_s1)
p0_s1 <- 1-p0_s0

2 R code snippets:calculate posterior probabilities using Bayes rule
p_s0_t[i] <- (f_s0[i] * p_s0_t_1[i]) / f[i]
p_s1_t[i] <- (f_s1[i] * p_s1_t_1[i]) / f[i]

Therefore the equation for the switching variance is

$$h_t^j = \gamma + \frac{\alpha}{g(S_{t-1} = j)}\left(\epsilon_{t-1}^j\right)^2 + \beta \hat{h}_{t-1}$$

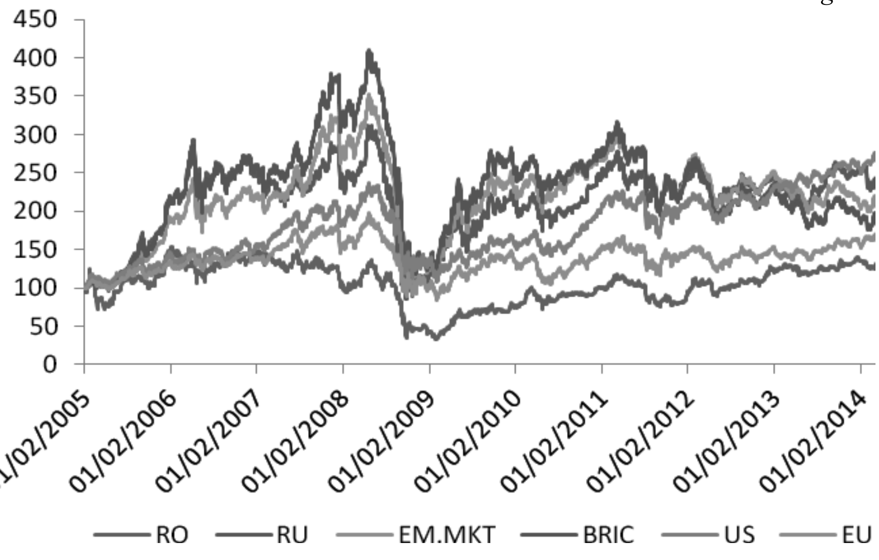
where β and γ are constants and $g(S = 1)$ is normalized to one.

ESTIMATION RESULTS

The dataset includes daily data for energy indices for the following markets: Russia, Emerging Markets, BRIC countries, United States and European Union. The Romanian energy index was included in order to facilitate the comparison and see the measure in which it is influenced the significant energy markets. Stock energy indices were obtained from Datastream Thompson database from January 2004 to January 2015. Daily returns are calculated from the stock market indices according to the formula $R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$ where P_t is the daily closing price of the index.

Closing prices for Oil&Gas total return index for Romania, Russia, Emerging Markets, BRIC countries, United States and European Union

Figure 1



Source: Thomson Reuters Datastream

The prices and the log returns of the indices show excess kurtosis meaning that the data is heavy-tailed and not normal distributed. The log returns are negatively skewed. While the characteristics of the log return series justify the investigation with a GARCH model[1] it remains to be analyzed if the indices have a nonlinear dynamics. The Markov Switching GARCH models can model the conditional variance if there are different volatility regimes.

Since the GARCH models work only with stationary time series, we have tested the log-returns of the indices with the Augmented Dickey Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test in order to estimate the presence of a unit root.

The ADF tests rejected the null hypothesis of a unit root process and the KPSS test accepted the null hypothesis of a stationary process. Both tests come to the same conclusion for all time series at high significance levels. We did not present tables with the test statistics, the p-values and the used lag orders for both stationarity tests for presentation reasons.

The GARCH models results show that the asymmetrical term (noted with 'D' in the Annex in the first section titled 'GARCH results') is not statistically significant for United States and European Union.

Regime 0 is considered a "bull market", while regime 1 is considered as ''bear market''. Using the Markov Switching Garch model we have estimated the mean equation parameters, an intercept and an AR lag, the GARCH model parameters and the Markov switching parameters. The terms $g(S_t = 0)$ and $g(S_t = 1)$ are the relative variances in the regimes also known as the variance inflations

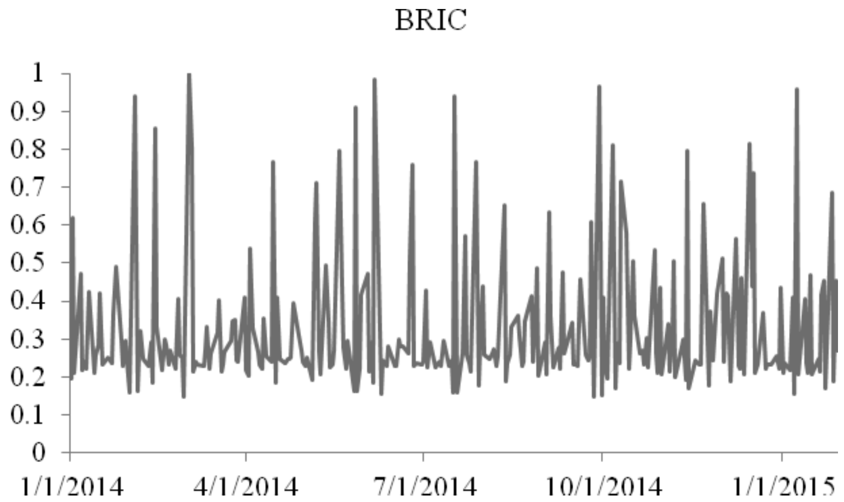
Only the results for Emerging Markets and BRIC countries seem to indicate a switching dynamic in the daily returns, while the results for the other indices have parameters which are not statistically significant . In figure 2 we have plotted the probability of being in the high volatility regime for BRIC countries and for Emerging Markets for one year starting with January 2014.

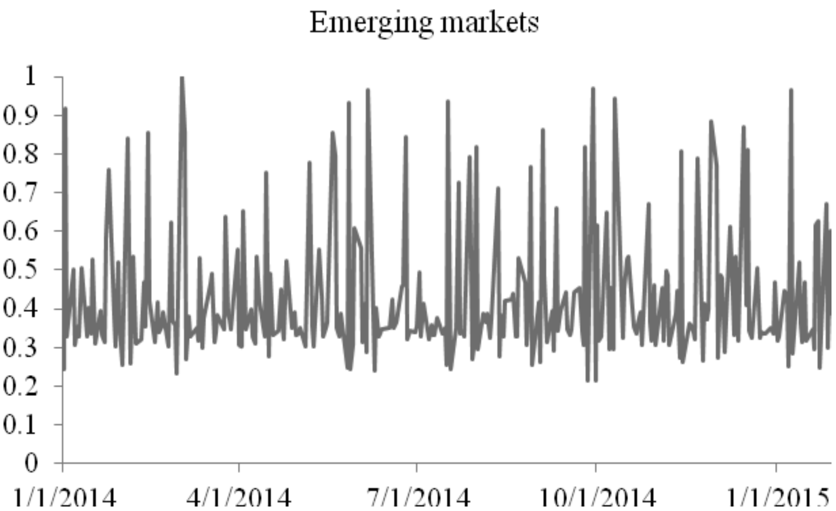
1 R code snippets:fitting a GJR-GARCH model

```
spec = ugarchspec(variance.model = list(model = " "gjrGARCH"), distribution.model = "std")
results_RO = ugarchfilter(spec = spec, data = ROM)
 show(results_RO)
```

The probability of high volatility regime for BRIC and Emerging Markets estimated by a MS-GARCH model

Figure 2





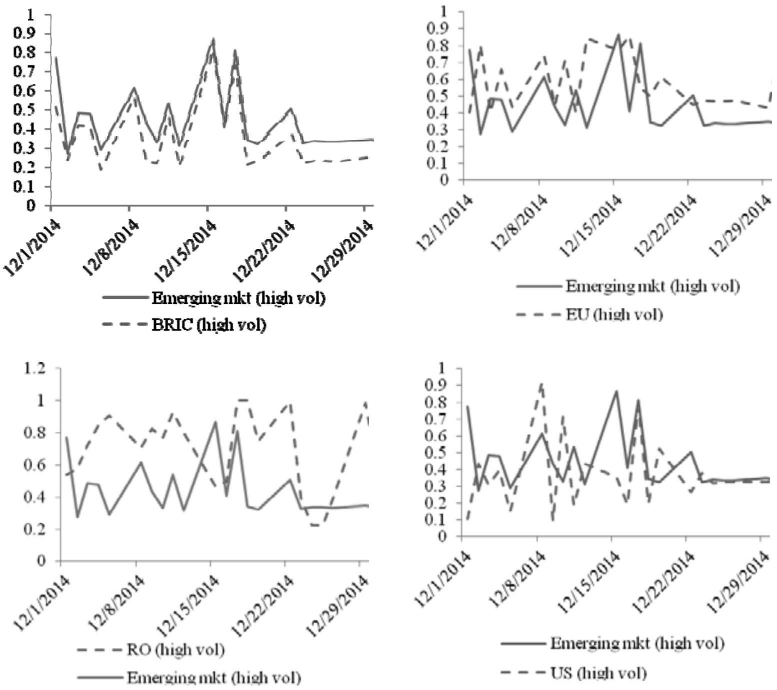
Oil prices fall in December led to a significant decrease in the energy sector on major international markets. In Europe, the FTSE index fell by 2.5%, the biggest drop since August 2011 due to lower revenue expectations for energy companies (BP, BG and Petrofac). In the last week of 2014 Brent oil price reached the minimum of the five last years after the IEA (International Energy Agency) has revised down forecasts for 2015. The energy sector SP500 index was hardest hit, with a fall of 18% in early October.

CBOE VIX and SP500 indexes fell sharply in the last weeks of the year 2014. Due to the decline of quotations for Brent, SP500 index recorded the strongest decrease in the last two and a half years while the US economy has seen a sustained growth pace as compared to other developed economies. The decrease in aggregate global demand signals a low growth for the global economy in 2015 and reduced inflationary expectations.

Although the long-term probabilities suggest heterogeneity in the energy indices, we may see that during a stressful environment, the energy indices respond simultaneously to the decrease in the oil prices thus indicating a clear dependency and sensitivity to oil price. The European Union energy index has a similar pattern with the Emerging Markets and BRIC countries. In figure 3 we have plotted the high volatility regime for Emerging Markets, BRIC countries, European Union, United States and Romania.

High probability regime of energy indices for December 2014

Figure 3



All computations were carried out in R. We used the following R packages: zoo, markovchain, timeSeries, rugarch.

CONCLUSIONS

In this paper we studied the short-term behavior of energy indices returns which is of particular importance for understanding the transition dynamics in energy markets. In addition to the GARCH models, Markov-switching GARCH models may indicate if the energy indices display a switching behavior and also if their dynamics is correlated with external risk factor.

Due to the heterogeneity of the companies included in the energy equity indices, the results suggest that changes in the volatility level and regime duration vary very much across countries since they are exposed to multiple risk factors.

The results do not show on the long run any clear pattern emerging but on the short run when there sudden and strong shocks occur there are overlapping patterns in the high volatility regime. Therefore the energy indices have reacted simultaneously to the decrease in the oil prices in December 2014 thus indicating a clear dependency and sensitivity to oil price. The European Union energy index had a similar pattern with the Emerging Markets and BRIC countries on December 2014.

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ANNEX 1

GARCH RESULTS

ROMANIA

Variable	Coeff	Std Error	T-Stat	Signif
Constant	0.0356	0.0283	1.2582	0.2083
y_{t-1}	-0.0019	0.0228	-0.0828	*0.9340*
α	0.0551	0.0150	3.6801	0.0002
D	0.0693	0.0144	4.7977	0.0000
β	0.9010	0.0134	67.1439	0.0000

Russia

Variable	Coeff	Std Error	T-Stat	Signif
Constant	0.0589	0.0305	1.9317	0.0534
y_{t-1}	-0.0027	0.0224	-0.1193	*0.9051*
α	0.0819	0.0152	5.4018	0.0000
D	0.0466	0.0089	5.2432	0.0000
β	0.8923	0.0125	71.1838	0.0000

Emerging Markets

Variable	Coeff	Std Error	T-Stat	Signif
Constant	0.0337	0.0233	1.4455	0.1483
y_{t-1}	0.1837	0.0210	8.7541	0.0000
α	0.0497	0.0104	4.7872	0.0000
D	0.0479	0.0107	4.4902	0.0000
β	0.8775	0.0143	61.2611	0.0000

BRIC Countries

Variable	Coeff	Std Error	T-Stat	Signif
Constant	0.0354	0.0285	1.2418	0.2143
y_{t-1}	0.1522	0.0208	7.3079	0.0000
α	0.0858	0.0158	5.4388	0.0000
D	0.0420	0.0097	4.3407	0.0000
β	0.8746	0.0148	59.1797	0.0000

United States

Variable	Coeff	Std Error	T-Stat	Signif
Constant	0.0510	0.0237	2.1562	0.0311
y_{t-1}	-0.0279	0.0221	-1.2627	0.2067
α	0.0235	0.0062	3.7839	0.0002
D	0.0159	0.0101	1.5677	*0.1170*
β	0.9274	0.0092	100.6593	0.0000

European Union

Variable	Coeff	Std Error	T-Stat	Signif
Constant	0.0254	0.0230	1.1036	0.2698
y_{t-1}	0.0169	0.0204	0.8270	0.4083
α	0.0263	0.0068	3.8458	0.0001
D	0.0159	0.0085	1.8715	*0.0613*
β	0.9272	0.0105	88.1574	0.0000

MARKOV SWITCHING - GARCH MODEL

Romania

Variable	Coeff	Std Error	T-Stat	Signif
p_{11}	0.7241	0.0535	13.5308	0.0000
p_{12}	0.2619	0.0581	4.5059	0.0000
γ	0.1002	0.0226	4.4349	0.0000
β	0.8608	0.0199	43.2824	0.0000
α	0.0484	0.0211	2.2893	0.0221
$\mu(S_t=0)$	0.0220	0.0267	0.8244	*0.4097*
$\mu(S_t=1)$	-0.0178	0.0203	-0.8756	*0.3813*
$\sigma(S_t=0)$	0.0167	0.0061	2.7319	0.0063
$\sigma(S_t=1)$	0.1054	0.0322	3.2714	0.0011

Russia

Variable	Coeff	Std Error	T-Stat	Signif
p_{11}	0.9746	0.0110	88.2027	0.0000
p_{12}	0.1804	0.0715	2.5235	0.0116
γ	0.0447	0.0114	3.9373	0.0001
β	0.9116	0.0115	79.0558	0.0000
α	0.0749	0.0190	3.9452	0.0001
$\mu(S_t=0)$	0.0585	0.0260	2.2499	0.0245
$\mu(S_t=1)$	-0.0171	0.0210	-0.8179	*0.4134*
$\sigma(S_t=0)$	0.0223	0.0060	3.7149	0.0002
$\sigma(S_t=1)$	0.1243	0.0382	3.2547	0.0011

Emerging Markets

Variable	Coeff	Std Error	T-Stat	Signif
p_{11}	0.4844	0.1287	3.7629	0.0002
p_{12}	0.6657	0.1257	5.2949	0.0000
γ	0.0647	0.0146	4.4243	0.0000
β	0.8594	0.0186	46.1499	0.0000
α	0.1066	0.0241	4.4240	0.0000
$\mu(S_t=0)$	0.0581	0.0196	2.9658	0.0030
$\mu(S_t=1)$	0.1665	0.0181	9.2157	0.0000
$\sigma(S_t=0)$	0.0209	0.0059	3.5508	0.0004
$\sigma(S_t=1)$	0.0693	0.0183	3.7982	0.0001

BRIC Countries

Variable	Coeff	Std Error	T-Stat	Signif
p_{11}	0.6252	0.2095	2.9844	0.0028
p_{12}	0.7593	0.1703	4.4582	0.0000
γ	0.0590	0.0138	4.2816	0.0000
β	0.8663	0.0213	40.7560	0.0000
α	0.0979	0.0248	3.9540	0.0001
$\mu(S_t=0)$	0.0611	0.0238	2.5700	0.0102
$\mu(S_t=1)$	0.1316	0.0212	6.1942	0.0000
$\sigma(S_t=0)$	0.0353	0.0094	3.7620	0.0002
$\sigma(S_t=1)$	0.1213	0.0306	3.9626	0.0001

United States

Variable	Coeff	Std Error	T-Stat	Signif
p_{11}	0.4763	0.1793	2.6556	0.0079
p_{12}	0.8472	0.1965	4.3111	0.0000
γ	0.0179	0.0122	1.4701	*0.1415*
β	0.9069	0.0115	78.7334	0.0000
α	0.1226	0.0211	5.8099	0.0000
$\mu(S_t=0)$	0.0806	0.0202	3.9918	0.0001
$\mu(S_t=1)$	-0.0279	0.0183	-1.5281	*0.1265*
$\sigma(S_t=0)$	0.0155	0.0044	3.5315	0.0004
$\sigma(S_t=1)$	0.0442	0.0120	3.6777	0.0002

European Union

Variable	Coeff	Std Error	T-Stat	Signif
p_{11}	0.3420	0.1392	2.4574	0.0140
p_{12}	0.4816	0.1240	3.8848	0.0001
γ	0.0178	0.0108	1.6511	0.0987
β	0.9216	0.0130	70.8434	0.0000
α	0.0978	0.0161	6.0642	0.0000
$\mu(S_t=0)$	0.0493	0.0229	2.1548	0.0312
$\mu(S_t=1)$	0.0048	0.0192	0.2516	*0.8013*
$\sigma(S_t=0)$	0.0092	0.0031	3.0139	0.0026
$\sigma(S_t=1)$	0.0299	0.0087	3.4296	0.0006