EVALUATION OF VOLATILITY OF CLEAN ENERGY STOCK PRICES IN A REGIME-SWITCHING ENVIRONMENT

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Abstract

Development of renewable energy companies may be strictly associated with the sector of new technology, the carbon permits market and the crude oil market. Therefore, we investigate the volatility dynamics of following time series: the Wilder Hill Clean Energy Index prices, the NYSE Arca Technology Index prices, the West Texas Intermediate crude oil prices, the ICE EUA Futures Contract Emissions Index prices in the period of 2006-2013. Empirical analysis is connected with construction of univariate Markov switching heteroskedasticity models with mean-variance component structure as well as with GARCH structure for each of analyzed variables. The Markov regime-switching model can detect switches in the volatility regimes of the returns and measure average duration of each variables in particular volatility regimes. These findings help investors to evaluate the risk associated with investment in clean energy companies shares and getting to know different risk factors.

Key words: clean energy stock prices, oil prices, carbon prices, Markov regime-volatility switching

JEL Code: G11, Q42, C58

Introduction

One of the vital elements of energy independence is the use of renewable energy sources. Renewable power industry constitutes the surest way leading to improvement of energy supplies security and reduction of environmnet pollution, including carbon dioxide emission into the atmosphere. Energy production cost from almost all renewable energy sources is still high. Therefore, development of renewable power industry needs state subsidies and legislatively imposed rigour of producing a defined part of energy from renewable sources. Production of electricity or heat from renewable energy sources requires investments in new technologies. In connection with this enterprises functioning in this market are searching for funds which are essential for development and innovations also through stock exchanges. Investors in turn, noticing the growing demand for energy, particularly for the renewable one, more and more frequently invest in the subjects of this trade. Surely, development of renewable power industry will vitally influence the market of oil and gas.

The International Energy Agency (IEA) predicts that renewable energy will be the fastest growing component of global energy demand. In many researchers' opinions, it is caused by climate changes and the necessity of the environment protection, the energy security issues, environmentally oriented consumers, the increasing of carbon permits prices and oil prices (Kumar, Managi and Matsuda, 2012; Sadorsky 2012; Henriques and Sadorsky, 2008; Managi and Okimoto, 2013). These researchers used different econometric tools in order to understand the prices' relationship among the sector of clean energy companies, new technology companies, crude oil market and carbon emission allowance market: VAR methodology (Henriques and Sadorsky, 2008; Kumar, Managi and Matsuda, 2012), Markov switching VAR (Managi and Okimoto, 2013), multivariate GARCH (Sadorsky 2012).

The goal of this paper is to examine and compare the volatility behavior of clean energy index, new technology index, carbon emission permits index and crude oil prices in the turbulent period, which covers the recession period after subprime financial crisis. To our knowledge, there is no study that examines the time-varying volatility process over different volatility regimes for the daily prices of renewable energy companies shares, new technology companies shares, crude oil and carbon emissions allowance. This paper differs from existing literature because we implemented Markov – switching model with mean-variance component structure and GARCH structure with two volatility regimes (low and high), as well as with three volatility regimes (low, moderate and high) for clean energy index prices and additional risk factors. The univariate Markov switching heteroskedasticity models can detect switches in the volatility states of the returns for each of analyzed variables and enable to measure average duration of each variables in particular volatility states (Hamilton and Susmel, 1994; Gray, 1996; Klaassen, 2002; Haas, Mittnik and Paolell, 2004; Włodarczyk and Zawada, 2006; Choi and Hammoudeh, 2010; Doornik, 2013).

1 Heteroskedasticity specification of Markov switching models

In order to achieve the goals stated in the introduction we take into consideration the following two classes of Markov switching models: one with mean-variance component

(Doornik, 2013a) and the other one with GARCH effect enabled (Haas, Mittnik and Paolella, 2004). The general form of p-th order Markov –switching autoregression model (MS-AR(p)) is given by the following equations (Doornik, 2013b):

$$y_t - \mu(s_t) = a_1(y_{t-1} - \mu(s_{t-1})) + a_2(y_{t-2} - \mu(s_{t-2})) + ... + a_p(y_{t-p} - \mu(s_{t-p})) + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2(s_t)) \quad (1)$$

where: y – endogenous variable, s_t – non-observable variable modelled as homogenous Markov chain of N states and the matrix of transition probabilities $P = \lfloor p_{i|j} \rfloor_{i,j \in \{0,1,2,...,N-1\}}$, determining the probability of moving endogenous variable from state *j* in period *t* into state *i* in period *t+1*, which additionally fulfil the following stochastic assumptions:

$$\sum_{i=0}^{N-1} p_{i|j} = 1, \qquad \mathrm{p_{i|j}} \geq 0 \quad \mathrm{for\, i, j = 0,1,...N\text{-}1}, \qquad (2)$$

$\mu(s_t)$ - conditional mean of the process, which is dependent on the regime variable s_t, a_i – the parameter describing the relationship between i-th order lagged and current values of endogenous variable.

Next authors incorporated GARCH structure into Markov switching model, which enables for different behaviour of the volatility process in particular regimes (Hamilton and Susmel,1994; Gray, 1996; Klaassen, 2002; Haas, Mittnik and Paolell, 2004)). In this paper we only consider the specification of the conditional variance equation for the MS-GARCH(1,1), constituting a generalization of the GARCH (1,1) model (Doornik, 2013b):

$$\varepsilon_t = \sqrt{h_t(S_t)} \cdot \nu_t, \quad \nu_t \sim \mathrm{N}(0,1), \qquad (3)$$

$$h_t(S_t) = \sigma^2(S_t) + \alpha_1(S_t)\varepsilon_{t-1}^2 + \beta_1(S_t)h_{t-1}(S_t), \quad \sigma^2(S_t) > 0, \alpha_1(S_t) \geq 0, \beta_1(S_t) \geq 0, \qquad (4)$$

where: $h_t(S_t)$ - regime dependent conditional variance of the error term; $\alpha_1(S_t)$ – regime dependent ARCH parameter depicting the reaction of volatility process on new market information; $\beta_1(S_t)$ - regime dependent GARCH parameter measuring the persistence of volatility process. Haas, Mittnik and Paolell (2004) proposed specification of the conditional variance equation with GARCH term which allows to avoid the problem of "regime path dependence" during the estimation procedures.

Taking into consideration the necessity to investigating the regime-switching process in conditional mean separately from the regime-switching process in conditional variance, what enables us to compare the level of fluctuations of mean and variance of endogenous variable in more accurate way, the following specification of Markov switching model is needed (Hamilton, 1994; Doornik, 2013b):

$$\begin{aligned} & y_t - \mu(s_{\mu,t}) = a_1(y_{t-1} - \mu(s_{\mu,t-1})) + a_2(y_{t-2} - \mu(s_{\mu,t-2})) + \ldots + a_p(y_{t-p} - \mu(s_{\mu,t-p})) + \varepsilon_t, \\ & \varepsilon_t \sim N(0, \sigma^2(s_{\sigma,t})) \end{aligned} \tag{5}$$

where: $s_{\mu,t}$ - non-observable variable modelled as homogenous Markov chain of N states and the matrix of transition probabilities $\mathbf{P}_\mu = \lfloor p_{i|j,\mu} \rfloor_{N \times N}$, which governs the regime –switching in mean; $s_{\sigma,t}$ - non-observable variable (modelled as homogenous Markov chain of N states and the matrix of transition probabilities $\mathbf{P}_\sigma = \lfloor p_{i|j,\sigma} \rfloor_{N \times N}$, which governs the regime –switching in variance; $s_{\mu,t}$ and $s_{\sigma,t}$ are independent variables. In order to simplify the structure of this model a new hidden variable s_t^* is introduced, modelled as homogenous Markov chain, and its states depend on the mean regime and the regime of y_t process variance. In case if only two regimes in the mean and two regimes in the process variance (N = 2) exist, the states of s_t^* variable can be defined as:

$$s_t^* = \begin{cases} 0 \, if \; s_{\mu,t} = 0, s_{\sigma,t} = 0 \\ 1 \, if \; s_{\mu,t} = 1, \; s_{\sigma,t} = 0 \\ 2 \, if \; s_{\mu,t} = 0, \; s_{\sigma,t} = 1 \\ 3 \, if \; s_{\mu,t} = 1, \; s_{\sigma,t} = 1 \end{cases} \tag{6}$$

and the matrix of transition probabilities for the s_t^* variable is of the following form (Doornik, 2013b):

$$\mathbf{P}^* = (p^*_{i|j}) = \left(\begin{array}{c|cccc} & s^*_t = 0 & s^*_t = 1 & s^*_t = 2 & s^*_t = 3 \\ \hline s^*_{t+1} = 0 & p_{0|0,\mu} \cdot p_{0|0,\sigma} & p_{0|1,\mu} \cdot p_{0|0,\sigma} & p_{0|0,\mu} \cdot p_{0|1,\sigma} & p_{0|1,\mu} \cdot p_{0|1,\sigma} \\ s^*_{t+1} = 1 & p_{1|0,\mu} \cdot p_{0|0,\sigma} & p_{1|1,\mu} \cdot p_{0|0,\sigma} & p_{1|0,\mu} \cdot p_{0|1,\sigma} & p_{1|1,\mu} \cdot p_{0|1,\sigma} \\ s^*_{t+1} = 2 & p_{0|0,\mu} \cdot p_{1|0,\sigma} & p_{0|1,\mu} \cdot p_{1|0,\sigma} & p_{0|0,\mu} \cdot p_{1|1,\sigma} & p_{0|1,\mu} \cdot p_{1|1,\sigma} \\ s^*_{t+1} = 3 & p_{1|0,\mu} \cdot p_{1|0,\sigma} & p_{1|1,\mu} \cdot p_{1|0,\sigma} & p_{1|0,\mu} \cdot p_{1|1,\sigma} & p_{1|1,\mu} \cdot p_{1|1,\sigma} \\ \hline \sum p^*_{i|\cdot} & 1 & 1 & 1 & 1 \end{array} \right) \tag{7}$$

The most frequently used method of parameter estimation in Markov-switching model is the maximum likelihood method (Hamilton, 1994; Klassen, 2002; Doornik, 2013b):

$$\ell(\theta) = \sum_{t=1}^{T} \ln \left[\sum_{i_0}^{N-1} \ldots \sum_{i_p=0}^{N-1} f\left(y_t \middle| s_t = i_0, \ldots, s_{t-p} = i_p, \Phi_{t-1}; \theta\right) \cdot P\left(s_t = i_0, \ldots, s_{t-p} = i_p \middle| \Phi_{t-1}; \theta\right) \right] \tag{8}$$

where the shape of the function of conditional distribution density of y variable depends on the "regime path dependence" $(s_t = i_0, \ldots, s_{t-p} = i_p)$ and the function of error term distribution density.[1]

Moreover, on the basis of estimated transition probabilities to particular volatility states (elements of the stochastic matrix **P**) one can determine expected further duration of the system in *i* regime: (Hamilton, 1994):

$$d_i = \frac{1}{1 - p_{i|i}} \quad (\mathrm{i} = 0, 1, \ldots, \mathrm{N} - 1) \tag{9}$$

where: d_i – average time of economic variable's duration in i-th regime.

2 Data description and identification volatility regime of clean energy stock prices

The data for this study includes the daily closing prices of the Wilder Hill Clean Energy Index (ECO)[2], the NYSE Arca Technology Index (PSE)[3], the West Texas Intermediate crude oil contract (WTI) and ICE EUA Futures Contract Emissions Index (CO2)[4] in the period from January 9, 2006 to June 31, 2013[5]. For each time series daily continuously compounded rates of return were computed, according to rules: $100 \cdot \ln(p_{i,t}/p_{i,t-1})$, where $p_{i,t}$ is daily closing price for i-th variable at *t* moment. Descriptive statistics and dynamic specification tests indicate for following properties of analysing returns series: volatility clustering, first order integration of returns series, fat tails and leptokurtic of returns distribution, skewness of empirical distributions, autocorrelation of returns[6].

Due to characteristic properties of indices returns and commodity returns we assumed that they would be described by a two-state Markov switching ARMA(2,q) model with mean-variance component structure and with Gaussian innovations. The second steps of our studies concerns the estimation of three-state Markov-switching ARMA(2,q) model with

[1] In the present paper the author assumed normal distribution of the error term due to computational power of PcGive 14 package, however this case can be generalized on any error distribution.
[2] http://www.wildershares.com/about.html (access 12.04.2014)
[3] http://www.nyse.com/pdfs/NYSEEuronext_ArcaTech100.pdf (access 12.03.2014)
[4] https://www.theice.com/marketdata/reports/ReportCenter.shtml?reportId=10&contractKey=20#report/82 (access 18.03.2014)
[5] All variables apart from the futures contract index market for permission to emit carbon dioxide, are denominated in USD, that is why we calculated the value of the index according to the valid on the same day last exchange rate of USD/EUR on the Forex market.
[6] Due to the size of the article, authors didn't present the table with the results of the statistics calculations.

GARCH(1,1) structure and also Gaussian innovations[7]. The purpose of MS(2)-ARMA(2,q) with mean-variance component model is to measure the switching of returns series between positive and negative mean regimes, which characterized bull and bear market, with simultaneous capturing the process switching between low and high volatility regimes (Table 1). In order to determine the number of regimes in Markov switching models we use regime classification measure (RCM), which was proposed by Ang and Bekaert (2002):

$$RCM(N) = 100 \cdot N^2 \cdot \frac{1}{T}\sum_{t=1}^{T}\left(\prod_{i=1}^{N} P(s_t = i \mid \Phi_{t-1})\right) \tag{10}$$

Tab. 1: Estimation of Markov switching model with mean-variance component structure (N=2)

Parameter/Statistic	**ECO**	**PSE**	**WTI**	**CO2**
Constant (0)	0.4417 [0.000]	0.6687 [0.000]	0.7629 [0.001]	0.2212 [0.039]
Constant (1)	-3.6027 [0.000]	-1.3923 [0.000]	-2.7051 [0.000]	-4.3867 [0.000]
AR-1	0.6999 [0.000]	0.6749 [0.000]	0.7385 [0.000]	0.5945 [0.000]
AR-2	-0.0738 [0.007]	0.0199 [0.531]	0.0275 [0.372]	-0.1092 [0.000]
MA-1	-0.6361 [0.000]	-0.7414 [0.000]	-0.7447 [0.000]	-0.4613 [0.000]
sigma (0)	1.5241 (0.0441)	0.8056 (0.0259)	1.5257 (0.0601)	1.7575 (0.0520)
sigma (1)	4.4523 (0.2495)	2.5432 (0.1241)	5.4311 (0.3361)	7.0872 (0.4446)
$p_{0\|0,\mu}$	0.9673 (0.0089)	0.9249 (0.0152)	0.9427 (0.0192)	0.9686 (0.0089)
$p_{1\|1,\mu}$	0.7691 (0.0461)	0.7406 (0.0391)	0.7136 (0.0789)	0.6594 (0.0670)
$p_{0\|0,\sigma}$	0.9979 (0.0017)	0.9973 (0.0012)	0.9950 (0.0022)	0.9884 (0.0034)
$p_{1\|1,\sigma}$	0.9871 (0.0092)	0.9843 (0.0076)	0.9543 (0.0186)	0.9253 (0.0211)
AIC	4.2554	3.1867	4.2911	4.6534
mean regime 0	33.17 / 90.69%[8]	14.50 / 81.60%	21.31 / 89.64%	42.79 / 94.48%
mean regime 1	3.47 / 9.31%	3.30 / 18.40%	2.49 / 10.36%	2.56 / 5.52%
variance regime 0	548.67 / 86.54%	323.00 / 84.91%	191.44 / 90.59%	104.00 / 87.49%
variance regime 1	128.00 / 13.46%	71.75 / 15.09%	22.38 / 9.41%	15.87 / 12.51%
Jarque-Bera test	6.131 [0.047]	6.435 [0.040]	29.979 [0.000]	23.372 [0.000]
Box-Pierce(40) test	48.493 [0.261]	38.366 [0.672]	37.691 [0.700]	43.433 [0.453]
ARCH(5) test	4.382 [0.001]	4.079 [0.001]	0.508 [0.770]	17.528 [0.000]
RCM	0.0334	0.0365	0.0522	0.0478

Source: Own calculations in PcGive 14. p-value in brackets and standard errors in parentheses.

Analyzing the average duration of the process in particular regimes we can observe that conditional mean of returns of the index ECO, PSE, WTI crude oil and contracts for carbon dioxide emission was subject to more frequent fluctuations than the conditional variance. The regime characterized by positive mean was the most permanent for the futures contracts market for CO2 emission permission (about 43 days) and investments in the

[7] We assume that the conditional mean follows an AR(2) process in order to capture non-synchronous trading effects.

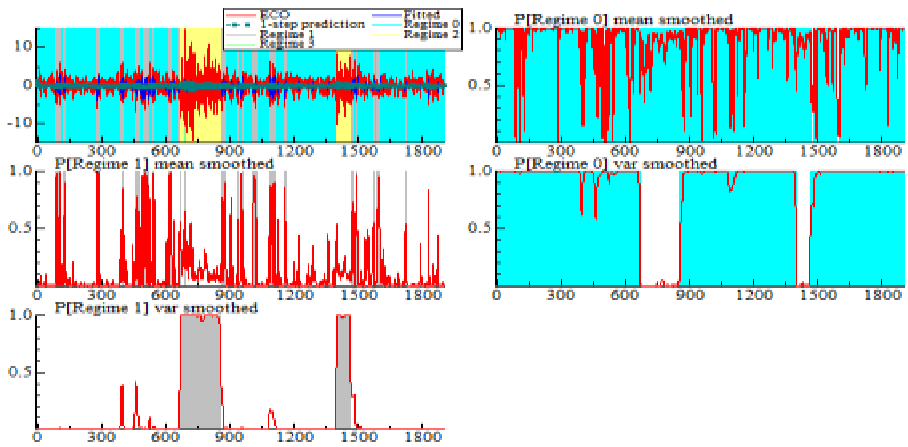
[8] The first number means the average duration (in days) of returns process in j-th regime, whilst the second one indicates the percentage of observations assigned to this regime.

renewable power industry sector (about 33 days), and it lasted the shortest in case of investments in the new technologies sector. Next the authors analyzed volatility ratio reflecting price fluctuations in the high and low volatility regime (σ_1/σ_0).

This ratio takes highest values for futures for permission for CO2 emission (4.03) and for WTI crude oil (3.56), which can indicate high sensitivity of these variables prices to switching to high volatility regime, and thus importance of the issue of protecting potential investors from price volatility on the crude oil and carbon dioxide market. Investments in the portfolio of partnerships from the ECO index in turn are charcterized by the lowest volatility coefficient oscilating around 2.92. In case of each variable analyzed in the paper variance regimes were relatively pernament, while definitely for stocks of companies connected with renewable power industry the high volatility regime lasted on average several times longer (128 days) than in case of the PSE index (about 72 days) or crude oil market (22 days) or the market of permissions for carbon dioxide emission (about 16 days). Thus, we can presume that rapid and unexpected changes of prices are more noticeable and more permanent on the capital market than on the commodity market (crude oil or carbon dioxide emission), similar depndencies were also observed in the low volatility level.

This was reflected at the time of the last subprime financial crisis when the ECO index after the rapid reduction at the beginning of March 2009 did not return to the previous price level.

Fig. 1: ECO returns and smoothed probabilities for each of mean and variance regime



Source: Own elaborations in PcGive 14.

We can see that the subprime financial crisis and the world recession, which was the consequences of it (2008-2009), had influenced the stock prices not only in clean energy sector, but also in new technology sector and strongly affected commodity markets. ECO index prices decreased about 71% and PSE index about 43% between August 22, 2008 and March 9, 2009. In turn, crude oil prices increased about 109% between August 21, 2007 and June 14, 2008, but in aftermath of the Lehman Brothers bankruptcy WTI crude oil prices decreased about 77% in the period from June 14, 2008 to February 18, 2009.

All determined for analyzed variables values of RCM statistics are low, which indicates correct classification of regimes in the estimated switching models. Figure 1 presents switching moments of the ECO index prices returns among particular regimes. It is worth noticing that observations coming from the period of subprime financial crisis (05.08.2008 – 05.06.2009) and the period 02.08.2011 – 02.11.2011 were attributed to regime 3 which represents the bear market (regime is characterized by negative mean and high volatility of returns). An interesting notion is also the evaluation of correlation between smoothed probabilities for regime 3 estimated on the basis of Markov-switching model for particular returns. Values of Pearson correlation coefficients indicate that the chances to change the valid regime of high volatility or process persistence in this regime are very similar for the ECO index and the PSE index (0.857) as well as for the ECO index and the WTI crude oil (0.654). Smoothed probabilities for regime 3 corresponding with the ECO index and contracts for permission for CO2 emission show very weak positive correlation (0.016), and what follows participants of the coal market may consider whether within price risk management they should not include stocks of renewable energy sector companies into their investment portfolios.

The values of estimated parameters of MS(3)-ARMA(p,q)-GARCH(1,1) class models with Gaussian innovations distribution presents Table 2.

Tab. 2: Estimation of Markov switching model with GARCH structure (N=3)

Parameter/Statistic	ECO	PSE	WTI	CO2
Constant (0)	0.777 [0.000]	0.662 [0.000]	1.500 [0.000]	0.718 [0.534]
Constant (1)	-0.704 [0.000]	-0.623 [0.000]	-0.414 [0.095]	-3.507 [0.004]
Constant (2)	-3.110 [0.080]	-1.984 [0.012]	-0.624 [0.227]	-18.216 [0.000]
AR-1(0)	0.596 [0.000]	0.556 [0.000]	0.770 [0.000]	1.103 [0.000]
AR-1(1)	-	-	0.314 [0.143]	-
AR-1(2)	-	-	-0.345 [0.302]	-
AR-2 (0)	-0.071 [0.007]	-0.038 [0.157]	0.0323 [0.486]	-0.147 [0.000]
AR-2 (1)	-	-	-0.019 [0.703]	-
AR-2 (2)	-	-	-0.107 [0.235]	-
MA-1 (0)	-0.550 [0.000]	-0.669 [0.000]	-0.809 [0.000]	-0.969 [0.000]
MA-1 (0)	-	-	-0.330 [0.104]	-
MA-1 (0)		-	0.386 [0.240]	-
sigma (0)	0.067 (0.099)	0.015 (0.080)	0.092 (0.073)	0.463 (0.061)

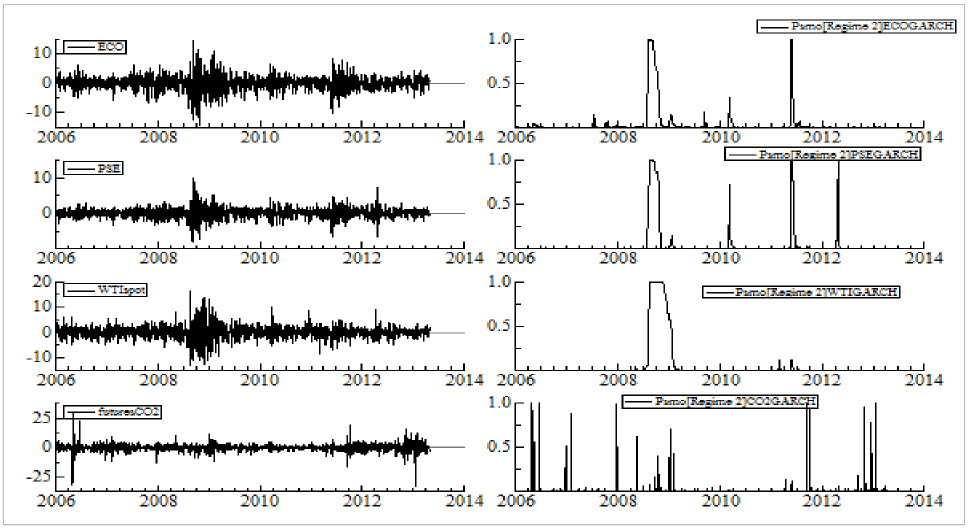
Parameter/Statistic	**ECO**	**PSE**	**WTI**	**CO2**
sigma (1)	0.208 (0.080)	0.166 (0.022)	0.316 (0.055)	0.860 (0.131)
sigma (2)	1.217 (1.478)	0.621 (0.096)	1.129 (0.195)	0.911 (0.257)
ARCH-1 (0)	0.0253 (0.012)	0.022 (0.006)	0.034 (0.010)	0.095 (0.021)
ARCH-1 (1)	0.0548 (0.023)	-	-	-
ARCH-1 (2)	0.0821 (0.233)	-	-	-
GARCH-1 (0)	0.9489 (0.023)	0.958 (0.008)	0.939 (0.016)	0.796 (0.036)
GARCH-1 (1)	0.9303 (0.022)	-	-	-
GARCH-1 (2)	0.8955 (0.316)	-	-	-
$p_{0\|0}$	0.88497	0.93166	0.90794	0.98276
$p_{1\|1}$	0.89500	0.89146	0.91369	0.97258
$p_{2\|2}$	0.94874	0.94645	0.98730	0.95072
AIC	4.1938	3.1282	4.2473	4.5473
variance regime 0	12.14 / 45.95%	20.91 / 62.67%	13.46 / 45.98%	69.08 / 43.59%
variance regime 1	13.22 / 50.74%	11.07 / 33.18%	13.76 / 47.71%	48.74 / 48.69%
variance regime 2	31.50 / 3.31%	19.75 / 4.15%	120 / 6.31%	18.38 / 7.73%
Jarque-Bera test	14.743 [0.001]	14.274 [0.001]	4.397 [0.111]	5.356 [0.069]
Box-Pierce(40) test	52.202 [0.159]	37.534 [0.707]	41.562 [0.534]	38.379 [0.672]
ARCH(5) test	0.372 [0.868]	4.809 [0.000]	0.439 [0.821]	0.556 [0.734]
RCM	0.750186	0.580131	0.603639	0.39672

Source: Own calculations in PcGive 14. p-value in brackets and standard errors in parentheses.

Three volatility regimes have been distinguished in the modelling: low volatility regime -0, moderate volatility regime -1, high volatility regime -2. Moreover, each of the three regimes is rather stable, as estimated transition probabilities from one to another regime are low (below 0.1). The longest period of high volatility regime duration was characteristic of WTI crude oil (almost 120 days). However only 6.31% of observations were assigned to this volatility state. For ECO index the expected period of remaining in the high volatility regime was almost 32 days. In case of ECO index the highest number of observations was assigned to the moderate volatility regime (50.74%), in which the process remained on average 13 days. PSE index on average remained the longest in the low volatility regime (20.91 days), and also most observations (62.67%) were assigned to this volatility regime. The most typical regime for WTI crude oil was the moderate volatility regime, taking into consideration the percentage of observations assigned to it (47.71%). For EUA futures contacts the highest number of observations was assigned to the moderate volatility regime (48.69%), in which the process remained on average 49 days.

The smoothed probabilities of high volatility regime for PSE returns and WTI returns are high correlated with these probabilities which were computed for ECO returns (appropriately 0.927 and 0. 648). Moreover, the periods of being returns process (ECO, PSE and WTI) in high volatility regime correspond to subprime financial crisis (Fig. 2).

Fig. 2: Returns series and smoothed probabilities of high volatility regime - MS-GARCH approach



Source: Own elaborations in PcGive 14.

Comparing the moments when the high volatility regime began and finished for each of the returns series we can indicate some similarities of their occurrence, connected with the impact of subprime financial crisis (August/September 2008 - April 2009). Moreover, the EUA Futures Contract returns are characterized by more frequent switching to high volatility regime than the remaining variables, which can be explained by the searching the balance level between the demand for allowances and the actual level of emissions, especially during I Phase of The European Union Emissions Trading Scheme (EU ETS) (the highest drop of prices was observed in April 2006).

Conclusion

Identifying regimes of low, moderate and high volatility for price returns of the ECO index, the PSE index, crude oil prices and contracts for permission for CO2 emission, combined with the estimated evaluation of average process duration in each regime may contribute to better protection of investors portfolios. Information of this type may be used while conducting diversification of the portfolio depending on the volatility regime. If companies included in the ECO index were interesting for the investors they would acquire additional funds for their development.

References

Ang, A., & Bekaert, G. (2002). Regime Switches in Interest Rates. *Journal of Business and Economic Statistics, 20*, 163-182.

Doornik, J. A. (2013a). A Markov-switching model with component structure for US GNP. *Economics Letters*, *118*, 265-268.

Doornik, J. A. (2013b). Econometric Analysis with Markov Switching Models. *PcGive 14*. London: Timberlake Consultants.

Gray, S. F. (1996). Modeling the conditional distribution of interest rates as a regime-switching process. *Journal of Financial Economics*, *3*, 27-62.

Haas, M., Mittnik, S., & Paolella, M. (2004). A New Approach to Markov-Switching GARCH Models. *Journal of Financial Econometrics*, *2*, 493-530.

Hamilton, J. D. (1994). *Time series analysis*. Princeton, N.J.: Princeton University Press.

Hamilton, J. D., & Susmel, R. (1996). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics*, *64*, 307-333.

Henriques, I., & Sadorsky, P. (2008). Oil price and the stock prices of alternative energy companies. *Energy Economics*, *30*, 998-1010.

Choi, K., & Hammoudeh, S. (2010). Volatility behavior of oil, industrial commodity and stock markets in a regime-switching environment. *Energy Policy*, *38*, 4388-4399.

Klaassen, F. (2002). Improving GARCH Volatility Forecasts with Regime-Switching GARCH. In J.D. Hamilton & B. Raj (Eds.), *Advances in Markov-Switching Models* (pp. 223-254). Heidelberg: Springer-Verlag.

Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics*, *34*, 215-226.

Managi, T., & Okimoto, T. (2013). Does the price of oil interact with clean energy prices in the stock market? *Japan and the World Economy*, 1-9.

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics*, *34*, 248-255.

Włodarczyk, A., & Zawada, M. (2006). Markov Switching Model as an example of non-stationary exchange rate model. *Dynamic Econometrics Model*, *7*, 239-248.

http://www.nyse.com/pdfs/NYSEEuronext_ArcaTech100.pdf (access 12.03.2014)

http://www.wildershares.com/about.html (access 12.04.2014)

https://www.theice.com/marketdata/reports/ReportCenter.shtml?reportId=10&contractKey=20#report/82 (access 18.03.2014)

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