A C T A U N I V E R S I T A T I S L O D Z I E N S I S
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THE IDENTIFICATION OF PERIODS WITH COMPARABLE RISK ON DAY AHEAD ELECTRIC ENERGY MARKETS IN POLAND

Abstract. In this paper the principal component analysis has been used to classify risk on day ahead electric energy markets in Poland. The multivariate statistical methods such as: principal component analysis are used. The risk is estimated by Value-at-Risk based on autoregressive time series.
Key words: energy market, classification, risk, principal component analysis, *VaR*, GARCH.

I. DAY AHEAD ELECTRIC ENERGY MARKETS

Day ahead electric energy markets in Poland include: Balance Market (BM), Day Ahead Market (DAM) and internet platform of electric energy turnover (poee). These markets function in various conditions. [1]

BM is a technical market, which balances the Polish energy market by means of Price Accounting Deviations (PAD). From 2002 year BM introduced additional prices, Price Accounting Deviations of sale (PADs) and Price Accounting Deviations of purchase (PADp). These prices should facilitate forecasting future demand for the electric energy on whole-day and futures market.

DAM works on the Polish Power Exchange (PPE). Electric energy price is established independently for each one of 24 hours a day before delivery. The price for each hour balances the aggregate supply and demand for this hour. The advantage of the exchange is that all participants of the market can buy and sell electric energy, irrespective of whether they are producers or receivers.

The participants of electric energy market can sell and purchase electric energy in day ahead system except DAM and BM on Day-Ahead Convention Energy Market of poee. PoDeeK index constructed as a weighted average price of every contract deal in this hour, is published on this market in every hour.

The aim of this article is the classification of risk on each of these three day ahead markets. The quotations from these markets from July to December 2007 are analyzed.

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[1] The quotations of these market are available on page: http://www.cire.pl/

II. PRINCIPAL COMPONENT ANALYSIS (PCA)

The Principal Component model is given by the following formula: (Grabiński (1992), Jajuga (1993), Ostasiewicz (1999)):

$$X = A^T Y . \tag{1}$$

where:
$X = [X_1, \quad X_2, \quad \dots \quad X_k]^T$ – vector of observed variables,
$Y = [Y_1, \quad Y_2, \quad \dots \quad Y_k]^T$ – vector of principal components,
$A = [a_1, \quad a_2, \quad \dots, \quad a_k]$ – orthogonal and normality matrix.

We determine Y making use of eigenvalues and eigenvectors of the covariance matrix of X. If we denote the eigenvalue of the i^{th} eigenvector U_i of the covariance matrix by λ_i, then we have:

$$D^2(Y_i) = \lambda_i \quad i = 1,...,k . \tag{2}$$

All observational variables are described by all principal components and by eigenvalues (2). If w_i denotes the contribution of Y_i to the explanation of X variables, then we can write:

$$w_i = \frac{\lambda_i}{\sum_{j=1}^{k} \lambda_j}, \quad i = 1, \dots, k. \tag{3}$$

In the model (1) only these principal components having the biggest share in explaining the variance of observational variables are used. In this paper criterion developed by Keiser was used, taking into account only principal components corresponding to eigenvalues greater than one (Ostasiewicz (1999)).

III. EMPIRICAL ANALYSIS

Three series of logarithmic rates of return of following electric energy prices: *PAD, DAM, poDeek,* which are quoted on these markets from July to December 2007 (4416 observations) are analyzed.

The electric energy volumes and prices are characterized by daily seasonal peaks and lows. *Seasonal Autoregressive Integrated Moving Average* (SARIMA) models with daily seasonal lag 24 are used to describe seasonality of all three time series (Ganczarek (2008)).

On each day ahead market, autocorrelation of the second moment of the data is observed. The *Generalized Autoregressive Conditional Heteroscedasticity (GARCH)* models are used to describe autocorrelation. For *PAD:* FIEGARCH(1,1,1) with t-Student distribution, for *DAM*: HYGARCH(1,1) with skewed t-Student distribution and for *poDeeK*: GARCH(1,1) with *Generalized Error Distribution (GED)*. All parameters of these models are statistically significant (Ganczarek(2008)).

Downside risk measures are more effective than the measures of volatility to estimate risk on the electric energy market, where the changes in prices and demand are quick and considerable (Trzpiot and Ganczarek(2006)). Therefore, in order to estimate risk on these markets, the *Value-at-Risk (VaR)* measure is used. It is calculated on the basis of the *GARCH* model. In table 1 p-values of the Kupiec test for VaR (Kupiec (1995)) are presented. The number of excesses of *VaR* is greater than expected only once for a long position (quantile 0,995 and 0,9975) on DAM and for short position (quantile 0,0025).

Table 1. The results of the Kupiec test for *VaR*, estimated using GARCH models

Theoretical quantile	p-values		
	PAD	DAM	poDeek
0,95	0,5514	0,0721	0,7587
0,975	0,5082	0,1041	0,4895
0,99	0,0577	0,7704	0,4478
0,995	0,3824	**<u>0,0095</u>**	0,1806
0,9975	0,7608	**0,0429**	0,5372
0,05	0,9696	0,8596	0,8117
0,025	0,1253	0,5510	0,7564
0,01	0,0577	0,9891	0,1056
0,005	0,0171	0,8244	0,0685
0,0025	0,0282	0,3443	**<u>0,0072</u>**

Source: Own calculation.

Next, based on result of $VaR_{0,05}$ estimation for short position, each $VaR_{0,05}$ time series was divided into 24 vectors corresponding to individual hours of the trading day. For each of these 24 vectors: $X = (X_1,\ldots, X_{24})$ the principal component analysis was used to classify the risk during a day. PCA eigenvalues and eigenvectors for X on every of three markets are presented in table 2.

To describe risk on BM six principal components were used. The first data set is described in 68% using these principal components. The set of the principal components loadings, can be interpreted as correlation coefficient between the original data value and the principal component. So the first principal component is correlated with hours from 18 to 21 more than other hours, while the second one is correlated with hours 5, 6, 14 more than other hours. The result in table 2 shows six different groups of risk. But based on first three principal components for BM one can identify three groups of risk (Figure 1). The first group includes hours from 3 to 6 (night). The second group includes hours 24, 1, 2 and from 7 to 16 (hours between two days and rush hours during a day). The third group includes hours 17 to 23 (evening).

Table 2. The results of the Kupiec test for *VaR* , estimated using GARCH models

X_j	PAD						DAM					poDeeK		
	U_1	U_2	U_3	U_4	U_5	U_6	U_1	U_2	U_3	U_4	U_5	U_1	U_2	U_3
1	0,01	0,04	0,06	0,04	0,11	**0,71**	0,34	0,05	0,21	0,11	**0,73**	0,24	**0,92**	0,24
2	0,09	-0,19	0,69	0,11	0,13	0,29	0,19	0,21	-0,02	0,07	**0,83**	0,26	**0,92**	0,23
3	0,05	0,02	**0,92**	0,04	0,16	0,00	0,14	0,10	0,14	0,38	0,64	0,29	**0,92**	0,24
4	0,05	0,31	**0,73**	0,10	0,13	0,01	0,12	0,06	0,16	**0,72**	0,30	0,32	**0,90**	0,27
5	0,10	**0,82**	0,42	0,06	-0,02	-0,02	0,10	0,23	0,21	**0,72**	0,12	0,34	**0,90**	0,27
6	0,02	**0,69**	0,51	0,08	0,00	0,00	0,22	0,32	-0,01	0,64	-0,04	0,42	**0,84**	0,24
7	0,06	0,25	0,42	0,18	-0,11	-0,08	0,11	0,27	0,03	0,60	0,10	0,53	**0,74**	0,31
8	0,04	0,03	0,15	**0,89**	0,05	0,02	0,13	**0,80**	0,02	0,28	0,09	**0,82**	0,45	0,32
9	0,10	0,12	0,11	**0,92**	0,18	0,04	-0,03	**0,87**	0,27	0,20	0,04	**0,88**	0,34	0,32
10	0,31	0,19	0,14	0,59	0,30	0,09	0,10	**0,80**	0,31	0,26	0,21	**0,88**	0,33	0,33
11	0,27	0,07	0,00	0,19	0,67	0,07	0,34	**0,69**	0,35	0,16	0,24	**0,88**	0,33	0,34
12	0,17	0,07	0,18	0,12	**0,82**	-0,02	0,47	0,39	0,45	0,25	0,31	**0,87**	0,33	0,35
13	0,25	0,11	0,17	0,02	**0,71**	-0,12	**0,82**	0,08	0,27	0,06	0,07	**0,87**	0,33	0,36
14	0,23	**0,78**	-0,09	0,07	0,19	-0,07	**0,81**	0,12	0,24	0,18	0,25	**0,87**	0,33	0,36
15	0,37	0,68	-0,11	0,16	0,36	0,21	**0,79**	0,07	0,13	0,12	0,26	**0,87**	0,33	0,36
16	0,40	0,43	-0,05	0,18	0,52	0,22	**0,86**	0,03	0,15	0,10	0,07	**0,86**	0,33	0,37
17	0,60	0,11	0,18	0,05	0,09	0,03	0,58	0,18	0,24	0,31	0,20	**0,86**	0,33	0,38
18	**0,84**	0,13	0,04	-0,02	-0,01	-0,11	0,20	0,01	0,61	0,49	0,18	**0,79**	0,32	0,49
19	**0,82**	0,30	0,06	0,08	0,11	-0,03	0,11	0,09	**0,82**	0,26	0,25	**0,69**	0,32	0,62
20	**0,84**	0,07	0,04	0,10	0,21	0,03	0,16	0,04	**0,83**	0,16	0,19	0,58	0,33	**0,73**
21	**0,78**	0,02	0,01	0,08	0,32	0,13	0,22	0,15	**0,81**	-0,03	-0,03	0,53	0,36	**0,76**
22	0,68	0,04	0,03	0,16	0,45	0,12	0,21	0,19	**0,81**	-0,10	-0,01	0,46	0,34	**0,81**
23	0,68	0,04	-0,04	0,13	0,45	0,12	0,36	0,29	0,55	0,13	0,02	0,44	0,33	**0,82**
24	0,07	-0,02	0,03	0,02	-0,11	**0,73**	0,16	0,39	**0,74**	0,18	0,01	0,44	0,33	**0,82**
λ_i	4,64	2,80	2,65	2,23	2,86	1,32	3,98	3,33	4,75	2,79	2,26	10,70	7,39	5,42
w_i	0,19	0,12	0,11	0,09	0,12	0,05	0,17	0,14	0,20	0,12	0,09	0,45	0,31	0,23
$\sum_{i=1}^{k_j} w_i$	0,19	0,31	0,42	0,51	0,63	**<u>0,68</u>**	0,17	0,31	0,51	0,63	**<u>0,72</u>**	0,45	0,76	**<u>0,98</u>**

Source: Own calculation.

Risk on DAM is explained in 72% using five principal components (Table 2). The first principal component is correlated with hours from 13 to 16 more than other hours, while the second one is correlated with hours from 8 to 11 more than other hours (rush hours). The third principal component is correlated with hours from 19 to 24 more than other hours (evening), and two last principal components are correlated with hours from 1 to 7 more than other hours (night). Based on first three principal components for DAM one can identify four groups of risk (Figure 2). The first group includes hours from 1 to 7 (night). The second group includes hours 8, 9, 10 (rush hour at morning). The third group includes hours from 13 to 17 (rush hours during a day). And the fourth group includes hours 11,12 and from 18 to 24 (generally evening).

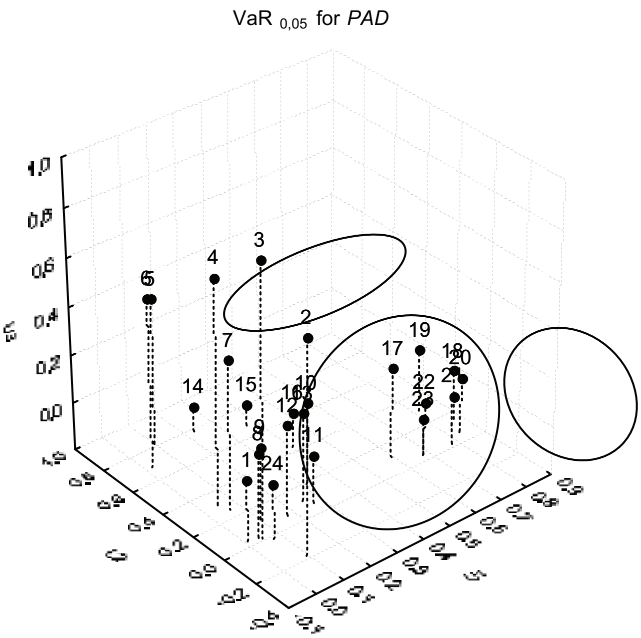

Figure 1. The classification of risk on Balance Market

Source: Own calculation.

VaR $_{0,05}$ for *DAM*

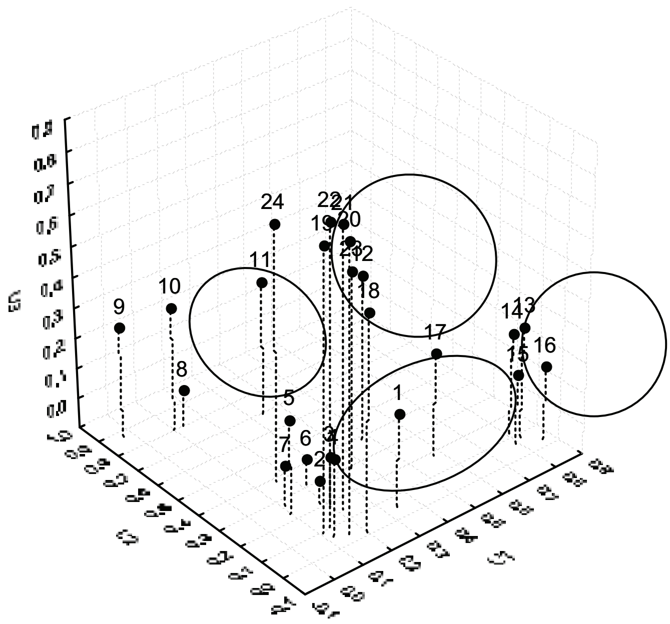

Figure 2. The classification of risk on Day Ahead Market

Source: Own calculation.

To describe risk on poee three principal components (Table 2) were used, which explained the last data set in 98%. The first principal component is correlated with hours from 8 to 19 (rush hour during a day) more than other hours (Table 2 and Figure 3), while the second one is correlated with hours from 1 to 7 (night) more than other hours (Table 2 and Figure 3), and the last one is correlated with hours from 20 to 24 (evening) (Table 2 and Figure 3).

VaR $_{0,05}$ for *poDeeK*

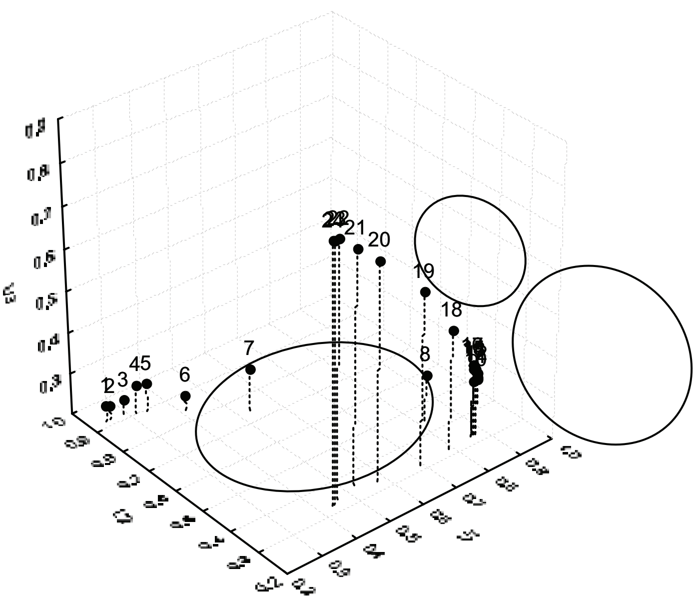

Figure 3. The classification of risk on internet platform of electric energy turnover
Source: Own calculation.

III. CONCLUSION

Electric energy prices and risk on day ahead markets depend on daily seasonality of volume. So one can divide hours of the day into groups respectively characterized by high or low level of risk. But classification results are different for each market.

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IDENTYFIKACJA OKRESÓW O ZBLIŻONYM RYZYKU NA DOBOWO GODZINNYCH RYNKACH OBROTU ENERGIĄ ELEKTRYCZNĄ W POLSCE

W oparciu o metody wielowymiarowe: analizę głównych składowych dokonano klasyfikacji ryzyka oszacowanego na poszczególnych dobowo godzinnych rynkach obrotu energią elektryczną. Do estymacji ryzyka wykorzystano kwantylowe miary zagrożenia Value at Risk oszacowane za pomocą autoregresyjnych szeregów czasowych.