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APPLICATIONS OF VaR AND CVaR METHODS ON ENERGY MARKET IN POLAND

Abstract. This article presents downside risk measures such as: Value-at-Risk – VaR and Conditional Value-at-Risk – CVaR. We establish them with three of the known methods. The electric energy is an article of real tame, which we can not store up and this influences on changes of price.

The downside risk measures are more effective than the measures of volatility for estimate risk on electric energy market. The aim this article is the choice of VaR and CVaR methods, that are the most effective for future risk on the Polish energy market. In this investigation we use the logarithmic rate of return of prices from the Polish Power Exchange, Balance Market (BM) from October to December 2002 and their simulation distributions.

Key words: Day Ahead Market, Balance Market, futures market, risk measures, Value-at-Risk, Conditional-Value-at-Risk, variance-covariance, Monte Carlo simulation, historical simulation, GED distribution.

1. INTRODUCTION

During the last few years Polish energy market has developed. The Polish Power Exchange came into existence. The Day Ahead Market (DAM) was the first market, which was established on the Polish Power Exchange. This whole-day market consists of the twenty-four separate, independent markets where participants can freely buy and sell electricity. The breakthrough in the development of the Polish Power Exchange was made July 1st 2000, when the first transaction were completed on the DAM. Advantage of the Exchange is that all the participants of market can buy and sell electric energy, independently whether there are producers or receivers of electric energy.

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Many of markets not equilibrium of demand and of supply balances across wrestling. But how do we store the electric energy? We can not do that. The electric energy is delivered only in the moment when demand for it appears. Since September 1st, 2001 has existed Balance Market (BM). This is technical market, which looks after balance on Polish energy market. Since July 1st, 2002 BM has introduced additional price, Price Accounting Deviations of sale PADs and Price Accounting Deviations of purchase PADp. These price should helpin expectation future demand for the electric energy on whole-day and futures market.

At present in Poland a forward energy market is developed still outside exchange. Since October 2002 on Polish Power Exchange we have had a futures market with the futures contracts on delivery of monthly, weekly and in peak-hours 7–10 p.m. electric energy.

The faster and the more considerable changes of price and demand, the greater is the risk on the market. Comparing daily change of price for petroleum 1–3%, for gas 2–4% with change of price for electric energy 10–50%, we see, that both producers and consumers of energy are forced to protect themselves against losses.

When we take financial decisions at the same time we take the risk. If we would like to estimate the future risk we have to measure it. There are a lot of different measures of risk. We can divide them into three groups: measures of volatility, measures of sensitivity and measures of downside risk. In this paper we present a few methods of measuring risk by two quantile measures: Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR).

2. VALUE-AT-RISK

We use downside risk measures to measure unwilling deviations from expected rate of return. One of them is VaR. VaR is such a loss of value, which could not exceed with the given probability $\alpha \in (0, 1)$.

$$P(W \leqslant W_0 - VaR) = \alpha \tag{1}$$

where W_0 is a present value, W is a random variable, value at the end of duration of investment.

VaR is a number that represents an estimate of how much we may lose due to market movements for a particular horizon and for a given confidence level. If we have the horizon and the degree of confidence, we must measure our risk Blanco (1998). There are three main methodologies to calculate VaR:

- Variance-covariance,
- Monte-Carlo simulation,
- Historical simulation.

The most commonly use of the three VaR methods is variance-covariance. It is based on the analysis of the volatilities and correlation between the different risks. The main issues that have to be solved in order to calculate analytic VaR are the following: the systematic measurement of actual markets for the production of data applicable to the vertex set chosen and the reduction of firm exposures to a form which can be analyzed using vertex dataset. In order to be compatible with the available data, every instrument in a portfolio needs to be reduced to collection of cash flows in order to derive a synthetic portfolio from the assets we hold. The synthetic portfolio is made up of positions in the risk factors or vertices for which we have volatilities and correlations. The main problem of this method is to have a set of risk factors small enough to be manageable, but comprehensive enough to capture the risk exposures of the firm. Once we construct the cash flow map, we only need to perform basic matrix manipulation to calculate the VaR of our portfolio Blanco (1998).

Monte Carlo simulation is based on the generation of random scenarios of prices for which the portfolio is revaluated. Looking at the hypothetical profits and losses under each scenario, it is possible to construct a histogram of expected profits and losses from which VaR are calculated. In this method we need a correlation and volatility matrix to generate the random scenarios. To perform Monte Carlo simulation it is necessary to have pricing models for all the instruments in our portfolio, and it is a procedure that is computationally intensive. The main advantage is that it is a forward-looking assessment of risk, and it deals with options and non-linear position as we conduct a full valuation of the portfolio for each price scenario Blanco (1998).

Historical simulation consists in revaluing the portfolio of several hundred historical scenarios and building a hypothetical distribution of profits and losses based on how the portfolio would have behave in the past. This simulation has the advantage that it does not use estimated on how variances and covariance, and we do not make any assumptions about the distribution of the portfolio returns. However, we assume that the past risk reflects the future risk, which in energy markets is a very extreme assumption. Historical simulation is definitely not the method to be used to capture risk on energy markets. To calculate VaR through historical simulation we need a database with historical prices for all the risk factors that we want to include in the simulation, and pricing models to revaluate the portfolio of each price scenario. We can think of historical simulation as a special case of the Monte Carlo simulation in which all the scenarios are defined *ex ante* according to the past behaviour of market prices Blanco (1998).

In Table 1 we compare this three methods. Each of them have some faults and some virtues.

Table 1. Methodologies to calculate VaR

Specification	Variance-covariance	Monte Carlo simulation	Historical simulation
1	2	3	4
Easiness of interpretation	Intuitive, although intermediate steps difficult to explain	Intuitive, but computational aspects more difficult to explain in a non-technical fashion	Very intuitive and easy to explain and interpret
Accuracy of VaR estimates	Depends on validity of assumptions (low optionally, stable variances-covariance, normality of return)	Depends on assumptions about variance and covariance, number of simulations and distribution of prices	Is the historical period choice representative of all possible future market scenarios?
Distributional assumptions about portfolio returns	Portfolio returns are independents and distributed normally	None, only distributional assumptions about risk factor returns to simulate random paths	None, but implicit assumption that past return behaviour is representative of future returns
Volatilities and correlation matrices	Required, correlation matrix must be positive-definite	Required, correlation matrix must be positive-definite	Not required
Amount of historical data needed for estimation of volatilities/correlation or for performing historical simulation	Exponentially weighted moving average methods require only a few months of historical data	Exponentially weighted moving average methods require only a few months of historical data.	Depends on market, structural changes, and seasonality effects
How does it deal with optionally?	Delta method. It can be a poor approximation for portfolios with strong optionally, specially with exotic options. Delta-gamma approach improves treatment but still not perfect	Full valuation approach, we can look at changes in volatilities as well as prices of the underlying from day to day	Full valuation approach
Data requirements	Can use risk metrics dataset or create own from historical price series	Can use risk metrics dataset or create own from historical price series	Absolute dependence on historical data, risk factors not represented in the dataset is ignored

Table 1. (condt.)

1	2	3	4
Analysis of VaR for risk management	Incremental and component VaR analysis possible, possible to go from risk measurement to risk management	Study of worst-case hypothetical scenarios, does not allow incremental VaR analysis	Absolute dependence on past events, does not allow incremental VaR analysis
Computational intensity/hardware requirements	Simple matrix multiplication once cash flow map is obtained, relatively fast for most portfolios	Computationally intensive, all the portfolio instruments must be revalued for each price scenario	Fairly easy to implement, but all instruments pricing functions are required
Length of horizon	Static approach, assumes portfolio is valued on the effective date of calculation, most effective for very short time horizons	Introduces the effects of time on portfolio returns mark-to-horizon	Can be adjusted, but there is a problem a data availability

The methods to calculate VaR – noticed by $Q_\alpha(W)$ α-quantile we can write:

$$Q_\alpha(W) = W_0 - VaR. \tag{2}$$

Noticed by $Q_\alpha(R)$ α-quantile of rate of return we can write:

$$Q_\alpha(R) = \frac{W_\alpha - W_0}{W_0} \quad \text{or} \quad Q_\alpha(R) = \ln\left(\frac{W_\alpha}{W_0}\right). \tag{3}$$

We have now

$$VaR = -Q_\alpha(R)W_0 \quad \text{or} \quad VaR = (1 - e^{Q_\alpha(R)})W_0. \tag{4}$$

Where R means rate of return, W_0 is a present value.

In variance-covariance method if we assume normal distribution of rate of return, we can write for example $VaR_{99\%} = -2.33\sigma W_0$, $VaR_{95\%} = -1.64\sigma W_0$, where σ – is a standard deviation of rates of return.

In Monte Carlo simulation $Q_\alpha(R)$ is α-quantile of rate of return, which is calculated from simulate distribution of rate of return. We use GED distribution with Generalized Error Distribution (Purczyński 2002):

$$f(x) = \frac{\lambda \cdot p}{2 \cdot \Gamma(\frac{1}{p})} \exp\{-\lambda^p |x-\mu|^p\}, \tag{5}$$

where

$\Gamma(z) = \int_0^\infty e^{-t} t^{z-1} dt$ is function of Gamma Euler,

p, μ, λ – are the parameters of this distribution.

For example if we take $p = 0.7$, GED is a t-student distribution, if $p = 1$ GED is a Laplaces' distribution with density function $f(x) = \frac{\lambda}{2} \exp\{-\lambda|x-\mu|\}$, for $p = 2$ GED is a normal distribution with density function $f(x) = \frac{\lambda}{\sqrt{\pi}} \exp\{-\lambda^2 (x-\mu)^2\}$. We can also estimate this parameter. An average is the estimator of μ (expected value).We estimate the parameter λ by maximum likelihood method (ML) and we have:

$$\lambda = \left(\frac{n}{p \sum_{i=1}^{n} |x_i|^p} \right)^{\frac{1}{p}}. \tag{6}$$

In historical simulation $Q_\alpha(R)$ is α-quantile of rate of return, which is calculated from historical rates of return.

The aim of this article is to choose such a method with best describes the Polish energy market. We use the failure test with a statistic proposed by Kupiec in 1995:

$$LR_{uc} = -2 \ln [(1-\alpha)^{T-N} \alpha^N] + 2 \ln \left\{ \left[(1 - \left(\frac{N}{T} \right) \right]^{T-N} \left(\frac{N}{T} \right)^N \right\} \tag{7}$$

where: N is a number of failure VaR, T is a length of sample, α is a significance level VaR. The LR_{uc} statistic have χ^2 distribution with one degree of freedom (Piontek 2002).

3. CONDITIONAL VALUE-AT-RISK

Next downside measure is CVaR. CVaR we can call Expected Shortfall – ES

$$ES_\alpha(X) = E\{X | X \leqslant Q_\alpha(X)\}. \tag{8}$$

The VaR quantity represents the maximum possible loss, which is not exceeded with the probability α. The CVaR quantity is the conditional expected loss given the loss strictly exceeds its VaR:

$$ES_\alpha(R) = E\{R \mid R \leqslant VaR_\alpha(R)\}. \tag{9}$$

CVaR is defined as the mean of the quantile of worst realizations. The definition ensures that the VaR is never more than the CVaR, so portfolios with low CVaR mast have low VaR as well.

CVaR is a function of α for fixed x.

For discrete distribution $\{(R_i, p_i)\ i = 1, ..., n\ \sum_{i=1}^{n} p_i = 1\}$ we can write:

$$ES_\alpha(R) = \frac{1}{\alpha}\sum_{i=1}^{k} R_i p_i, \quad \sum_{i=1}^{k} p_i = \alpha. \tag{10}$$

For continuous distribution with cumulative distribution function F_X we define this measure as:

$$ES_\alpha = \frac{1}{\alpha}\int_0^\alpha F_x^{(-1)}(t)dt \quad 0 < \alpha \leqslant 1, \tag{11}$$

where $F_x^{(-1)}(p) = \inf\{\eta;\ F_X(\eta) \geqslant p\}$ (Ogryczak, Ruszczyński 2002).

CVaR is alternative measure of risk, but has a better properties than VaR. CVaR is a coherent risk measure having the following properties: transition-equivariant, positively homogeneous, convex, monotonic, stochastic dominance of order 1, and monotonic dominance of order 2 (Pflug 2000).

Minimizing the CVaR of portfolio is closely related to minimizing VaR, as already observed from the definition of these measures. So CVaR have above properties, we should prefer this measure to optimize our portfolio.

Let U means running value of energy and R is a rate of return then we have:

CVaR for prices of electric energy:

$$CVaR_{99\%} = ES_{0.01}(R)U, \tag{12}$$

$$CVaR_{95\%} = ES_{0.05}(R)U. \tag{13}$$

4. THE VaR AND CVaR ON POLISH ENERGY MARKET

For estimation of risk on the Polish energy market we took under consideration of the logarithmic rate of return of contracts on electric energy and of electric energy on DAM and on BM noted from October

1st, 2002 to December 20th, 2002. In this part of paper we present the results of calculate VaR and CVaR and compare them.

Already in initial analysis in Table 2 we see, that on BM and DAM are higher changes in price than on futures market. When we look at Value at Risk we can say, that with probability 0.99 on contract FFM01-03 we will not lose more than 2.92 zł/MWh. We will not lose more than 10.06 zł/MWh on contract FFW50-03 with probability 0.95. In analogous period on whole-day market our losses with probability 0.99 will not exceed value from 11.48 to 88.43 zł/MWh, and from 8.08 to 62.24 zł/MWh with probability 0.95.

Table 2. Quantile downside risk measures – variance-covariance

Contracts on electric energy	s	U U(zł/MWh)	$VaR_{99\%}$	$VaR_{95\%}$	$ES_{0.01}$	$ES_{0.05}$	$CVaR_{99\%}$	$CVaR_{05\%}$
FFM01-03	0.01	125.43	–2.92	–2.06	–0.03	–0.02	–3.26	–2.56
FFW45-02	0.02	127.79	–5.96	–4.19	–0.05	–0.04	–6.65	–5.22
FFW46-02	0.04	125.59	–11.70	–8.24	–0.10	–0.08	–13.07	–10.26
FFW47-02	0.03	128.22	–8.96	–6.31	–0.08	–0.06	–10.01	–7.86
FFW48-02	0.04	125.77	–11.72	–8.25	–0.11	–0.09	–14.35	–11.54
FFW49-02	0.04	124.94	–11.64	–8.20	–0.10	–0.08	–13.00	–10.21
FFW50-02	0.05	122.73	–14.30	–10.06	–0.13	–0.10	–15.96	–12.54
FFW51-02	0.04	122.93	–11.46	–8.06	–0.10	–0.08	–12.79	–10.05
FFW52-02	0.03	116.35	–8.13	–5.72	–0.08	–0.06	–9.08	–7.13
PAD	0.13	107.09	–32.44	–22.83	–0.35	–0.28	–37.49	–29.45
PADs	0.12	236.67	–66.17	–46.58	–0.34	–0.27	–81.44	–63.97
PADp	0.06	82.12	–11.48	–8.08	–0.16	–0.13	–13.17	–10.34
DAM	0.35	108.44	–88.43	–62.24	–1.11	–0.87	–120.56	–94.69

The results obtained for $CVaR_{99\%}$ inform about average of the 1% the biggest loss. For example $CVaR_{99\%} = -3{,}26$ for FFM01-03 means, that the average of the 1% the worst loss equal 3.26 zł/MWh. Analogously $CVaR_{95\%} = -2.56$ means that the average of the 5% the worst loss on this contract equal 2.56 zł/MWh.

On DAM $VaR_{99\%} = -87.23$ informs, that on this market with probability 0.99 we can not lose more than 87.23 zł/MWh and with probability 0.01 we can lose more. With the same degree of confidence on this market $CVaR_{99\%} = -120.56$, informs that among 1% the worst loss we may average lost 120.56 zł/MWh.

We compare this result with measures VaR and CVaR calculated by Monte Carlo simulations and historical simulation, we can say, that results are analogous but not the same.

For the Monte Carlo simulations we use normal and GED distribution. In table 3–6 we represent expected values of downside risk measures, that we calculated by 1000 simulations. From distribution we random selection with replacement one hundred elements random sample. From each we calculate quantile and next we estimate quantile downside risk measures based on 1000 simulations.

Table 3. Quantile downside risk measures – Monte Carlo simulation (normal distribution)

Contracts on electric energy	Price	Quanrile		ES		VaR		CVaR	
	U	$Q_{0.01}$	$Q_{0.05}$	$ES_{0.01}$	$ES_{0.05}$	$VaR_{99\%}$	$VaR_{95\%}$	$CVaR_{99\%}$	$CVaR_{95\%}$
FFM01-03	125.43	–0.02	–0.02	–0.02	–0.02	–2.76	–2.03	–2.76	–2.35
FFW45-02	127.79	–0.04	–0.03	–0.04	–0.04	–5.67	–4.12	–5.67	–4.80
FFW46-02	125.59	–0.09	–0.06	–0.09	–0.07	–11.05	–8.09	–11.05	–9.39
FFW47-02	128.22	–0.07	–0.05	–0.07	–0.06	–8.52	–6.24	–8.52	–7.24
FFW48-02	125.77	–0.10	–0.08	–0.10	–0.09	–12.39	–9.47	–12.39	–10.76
FFW49-02	124.94	–0.09	–0.06	–0.09	–0.07	–11.04	–8.06	–11.04	–9.35
FFW50-02	122.73	–0.11	–0.08	–0.11	–0.09	–13.54	–9.89	–13.54	–11.51
FFW51-02	122.93	–0.09	–0.06	–0.09	–0.08	–10.90	–7.95	–10.90	–9.22
FFW52-02	116.35	–0.07	–0.05	–0.07	–0.06	–7.69	–5.63	–7.69	–6.52
PAD	107.09	–0.04	–0.03	–0.04	–0.04	–6.39	–4.68	–6.39	–5.44
PADs	236.67	–0.29	–0.21	–0.29	–0.25	–31.34	–22.81	–31.34	–26.54
PADp	82.12	–0.27	–0.20	–0.27	–0.23	–63.39	–46.51	–63.39	–53.93
DAM	108.44	–0.13	–0.10	–0.13	–0.11	–11.08	–8.10	–11.08	–9.42

For GED distribution we estimate the expected values μ with the averages of rates of return, and the parameters λ with formula (6). To take p value, we use result of estimate this distribution by Purczyński (2002) where $\hat{p} = 1.841$ (for $p = 2$ GED is a normal distribution). We take $p = 1$ (GED is a Laplaces' distribution) and $p = 0.7$ (GED is a t-student distribution) and compare them.

Table 4. Quantile downside risk measures – Monte Carlo simulation (GED $p = 1.841$)

Contracts on electric energy	Price	Quanrile		ES		VaR		CVaR	
	U	$Q_{0.01}$	$Q_{0.05}$	$ES_{0.01}$	$ES_{0.05}$	$VaR_{99\%}$	$VaR_{95\%}$	$CVaR_{99\%}$	$CVaR_{95\%}$
FFM01-03	125.43	–0.03	–0.02	–0.03	–0.02	–3.27	–3.00	–3.27	–3.14
FFW45-02	127.79	–0.11	–0.10	–0.11	–0.10	–13.88	–12.71	–13.88	–13.30
FFW46-02	125.59	–0.18	–0.17	–0.18	–0.17	–22.90	–20.99	–22.90	–21.95
FFW47-02	128.22	–0.14	–0.13	–0.14	–0.14	–18.10	–16.60	–18.10	–17.35
FFW48-02	125.77	–0.19	–0.18	–0.19	–0.18	–23.97	–22.12	–23.97	–23.04
FFW49-02	124.94	–0.16	–0.15	–0.16	–0.16	–20.59	–18.85	–20.59	–19.73
FFW50-02	122.73	–0.20	–0.18	–0.20	–0.19	–24.42	–22.35	–24.42	–23.38
FFW51-02	122.93	–0.18	–0.17	–0.18	–0.17	–22.21	–20.37	–22.21	–21.29
FFW52-02	116.35	–0.15	–0.14	–0.15	–0.14	–17.43	–15.97	–17.43	–16.71
PAD	107.09	–0.55	–0.50	–0.55	–0.52	–58.43	–53.53	–58.43	–55.96
PADs	236.67	–0.50	–0.46	–0.50	–0.48	–119.12	–109.55	–119.12	–114.37
PADp	82.12	–0.26	–0.24	–0.26	–0.25	–21.68	–19.82	–21.68	–20.75
DAM	108.44	–1.23	–1.13	–1.23	–1.18	–133.63	–122.42	–133.63	–128.06

Table 5. Quantile downside risk measures – Monte Carlo simulation (GED $p = 1$)

Contracts on electric energy	Price	Quanrile		ES		VaR		CVaR	
	U	$Q_{0.01}$	$Q_{0.05}$	$ES_{0.01}$	$ES_{0.05}$	$VaR_{99\%}$	$VaR_{95\%}$	$CVaR_{99\%}$	$CVaR_{95\%}$
FFM01-03	125.43	–0.02	–0.02	–0.02	–0.02	–2.92	–2.67	–2.92	–2.80
FFW45-02	127.79	–0.17	–0.15	–0.17	–0.16	–21.47	–19.65	–21.47	–20.54
FFW46-02	125.59	–0.26	–0.24	–0.26	–0.25	–33.22	–30.47	–33.22	–31.84
FFW47-02	128.22	–0.10	–0.09	–0.10	–0.10	–13.23	–12.18	–13.23	–12.71
FFW48-02	125.77	–0.31	–0.28	–0.31	–0.30	–38.93	–35.79	–38.93	–37.39
FFW49-02	124.94	–0.26	–0.23	–0.26	–0.25	–32.06	–29.34	–32.06	–30.66
FFW50-02	122.73	–0.30	–0.27	–0.30	–0.29	–36.58	–33.57	–36.58	–35.05
FFW51-02	122.93	–0.25	–0.23	–0.25	–0.24	–30.51	–28.08	–30.51	–29.29
FFW52-02	116.35	–0.20	–0.19	–0.20	–0.20	–23.72	–21.73	–23.72	–22.74
PAD	107.09	–0.68	–0.62	–0.68	–0.65	–72.30	–66.34	–72.30	–69.30
PADs	236.67	–0.62	–0.57	–0.62	–0.59	–145.88	–133.99	–145.88	–140.03
PADp	82.12	–0.35	–0.32	–0.35	–0.33	–28.64	–26.36	–28.64	–27.50
DAM	108.44	–0.91	–0.84	–0.91	–0.87	–98.74	–90.73	–98.74	–94.72

Table 6. Quantile downside risk measures – Monte Carlo simulation (GED $p = 0.7$)

Contracts on electric energy	Price	Quanrile		ES		VaR		CVaR	
	U	$Q_{0.01}$	$Q_{0.05}$	$ES_{0.01}$	$ES_{0.05}$	$VaR_{99\%}$	$VaR_{95\%}$	$CVaR_{99\%}$	$CVaR_{95\%}$
FFM01-03	125.43	-0.02	-0.02	-0.02	-0.02	-2.52	-2.32	-2.52	-2.41
FFW45-02	127.79	-0.24	-0.22	-0.24	-0.23	-30.91	-28.36	-30.91	-29.62
FFW46-02	125.59	-0.37	-0.34	-0.37	-0.35	-46.37	-42.49	-46.37	-44.43
FFW47-02	128.22	-0.08	-0.07	-0.08	-0.08	-10.23	-9.36	-10.23	-9.80
FFW48-02	125.77	-0.54	-0.49	-0.54	-0.52	-67.78	-62.20	-67.78	-64.99
FFW49-02	124.94	-0.34	-0.32	-0.34	-0.33	-43.01	-39.39	-43.01	-41.20
FFW50-02	122.73	-0.40	-0.37	-0.40	-0.38	-49.10	-45.01	-49.10	-47.05
FFW51-02	122.93	-0.32	-0.29	-0.32	-0.31	-39.41	-36.15	-39.41	-37.77
FFW52-02	116.35	-0.26	-0.24	-0.26	-0.25	-30.71	-28.17	-30.71	-29.43
PAD	107.09	-0.87	-0.80	-0.87	-0.84	-93.59	-85.86	-93.59	-89.72
PADs	236.67	-0.78	-0.72	-0.78	-0.75	-185.54	-170.41	-185.54	-177.96
PADp	82.12	-0.48	-0.44	-0.48	-0.46	-39.07	-35.82	-39.07	-37.45
DAM	108.44	-1.03	-0.94	-1.03	-0.99	-111.76	-102.45	-111.76	-107.12

Table 7. Quantile downside risk measures – historical simulation

Contracts on electric energy	Price	Quanrile		VaR		CVaR	
	U	$Q_{0.01}$	$Q_{0.05}$	$VaR_{99\%}$	$VaR_{95\%}$	$CVaR_{99\%}$	$CVaR_{95\%}$
FFM01-03	125.43	-0.03	-0.01	-3.18	-1	-3.18	-1.91
FFW45-02	127.79	-0.05	-0.05	-6.63	-5.72	-6.63	-6.18
FFW46-02	125.59	-0.13	-0.09	-14.82	-11.22	-14.82	-13.04
FFW47-02	128.22	-0.17	-0.02	-20.25	-2.89	-20.25	-11.89
FFW48-02	125.77	-0.14	-0.1	-16.95	-12.24	-16.95	-14.62
FFW49-02	124.94	-0.06	-0.06	-7.17	-7.17	-7.17	-7.17
FFW50-02	122.73	-0.12	-0.06	-13.46	-7.5	-13.46	-10.52
FFW51-02	122.93	-0.12	-0.05	-13.48	-6.04	-13.48	-9.82
FFW52-02	116.35	-0.11	-0.05	-11.91	-5.93	-11.91	-8.96
PAD	107.09	-0.45	-0.21	-38.82	-19.91	-46.52	-31.33
PADs	236.67	-0.4	-0.19	-77.56	-40.55	-95.9	-65.17
PADp	82.12	-0.19	-0.1	-14.38	-7.78	-16.69	-11.72
DAM	108.44	-0.3	-0.17	-28.5	-16.98	-34.88	-24.94

In Table 7 we introduce downside risk measures, that was calculated by historical simulation. All methods show that the risk is bigger on whole-day market than on futures market. VaR and CVaR measures are difference for difference methods, but CVaR does not exceed the value of VaR in every case (9). And for bigger confidence level $(1-\alpha)100\%$ we have lower measures.

5. CONCLUSION

In conclusion we compare all the result of these measures. In Tables 8 and 9 we introduced the values of Kupiec's statistics given in formula (7) with significance level $\alpha = 0.01$ and $\alpha = 0.05$. We mark there of them, if we can say that probability failure VaR equals significance level VaR. Some values of VaR are so low, that they are lower than real rates of return noted in this part of time on futures and whole-day market. For them we do not calculate values of statistic LR_{uc}.

Table 8. Values of statistic LR_{uc} given in formula (7) with significance level $\alpha = 0.01$

Contracts on electric energy	Variance-covariance	Monte Carlo simulation				Historical stimulation
		normal distribution	GED $p = 1.841$	GED $p = 1$	GED $p = 0.7$	
FFM01-03	2.315	2.315	–	2.315	2.315	–
FFW45-02	3.382	* 9.073	–	–	–	3.382
FFW46-02	* 8.512	* 8.512	–	–	–	–
FFW47-02	2.945	2.945	2.945	2.945	2.945	2.945
FFW48-02	* 13.385	* 7.543	–	–	–	2.747
FFW49-02	–	–	–	–	–	–
FFW50-02	–	3.382	–	–	–	–
FFW51-02	3.141	3.141	–	–	–	–
FFW52-02	2.902	2.902	–	–	–	–
PAD	* 159.174		* 29.507	* 32.346	* 40.584	* 45.798
PADs	* 155.246	* 132.420	* 28.047	* 30.635	* 38.173	* 41.854
PADp	* 159.174	* 34.736	* 32.346	* 38.173	* 40.584	* 47.902
DAM	* 41.854		* 213.142	* 29.507	* 29.507	* 75.926

With significance level $\alpha = 0.01$ and one degree of freedom $\chi^2 = 6.635$, all methods of calculation VaR are good for measure risk on whole-day market without Monte Carlo simulation with normal distribution (for this method the number of failure VaR equals 433/2208 for PAD and 189/2208 for DAM). On futures market we say only that probability failure VaR for. FFW45-02 was calculated by Monte Carlo simulation with normal distribution, FFW46-02 and FFW48-02 were calculated by variance-covariance method and Monte Carlo simulation with normal distribution equals 0.01.

Table 9. Values of statistic LR_{uc} given in formula (7) with significance level $\alpha = 0.05$

Contracts on electric energy	Variance-covariance	Monte Carlo simulation				Historical stimulation
		normal distribution	GED $p = 1.841$	GED $p = 1$	GED $p = 0.7$	
FFM01-03	* 6.604	* 6.604	* 6.604	* 6.604	* 6.604	* 10.544
FFW45-02	* 10.806	* 10.806	–	–	–	* 5.196
FFW46-02	* 10.575	* 10.575	–	–	–	* 10.575
FFW47-02	* 5.420	* 5.420	* 5.420	* 5.420	* 5.420	* 10.432
FFW48-02	* 16.107	* 16.107	* 3.970	* 3.970	* 3.970	* 10.347
FFW49-02	–	–	–	–	–	–
FFW50-02	* 5.196	* 5.196	–	–	–	* 10.806
FFW51-02	* 5.286	* 5.286	–	–	–	* 10.575
FFW52-02	* 10.408	* 10.408	–	–	–	* 10.408
PAD	* 568.504		* 213.374	* 210.261	* 222.672	* 568.504
PADs	* 528.229	* 503.688	* 211.405	* 210.261	* 220.219	* 548.216
PADp	* 578.759	* 213.374	* 211.146	* 220.219	* 220.219	* 578.759
DAM	* 210.646			* 210.646	* 210.646	* 615.203

With significance level $\alpha = 0.05$ and one degree of freedom $\chi^2 = 3.841$, the methods of calculation of VaR are good for measure risk on futures and whole-day market without Monte Carlo simulation with normal distribution (for this method the number of failure VaR equal 503/2208 for PAD and 269/2208 for DAM) and Monte Carlo simulation with GED distribution when $p = 1.841$ (186/2208 failure VaR for DAM). We can say, that probability failure VaR was calculated by the proposed method with significance level $\alpha = 0.05$ equals 0.05 without PAD and DAM.

In conclusion we can say, that VaR with significance level $\alpha = 0.05$ is more precise and probability failure VaR equals 0.05 almost for all values of VaR.

Monte Carlo simulation shows, that the fat-tailed distributions better describe VaR for energy prices on the Polish energy market. And we can say, that for logarithmic rate of return of contracts on electric energy and of electric energy on DAM and on BM noted from Octaber 1st to December 12th, 2002 for $\alpha = 0.01$ VaR and CVaR variance-covariance method is sufficient and for $\alpha = 0.05$ the method of historical simulation too. So we have a choice between VaR and CVaR.

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Alicja Ganczarek

ZASTOSOWANIE METOD VaR ORAZ CVaR NA RYNKU ENERGII W POLSCE

(Streszczenie)

Podejmując decyzje związane z przyszłością, podejmujemy ryzyko. Ocena ryzyka jest oceną subiektywną i w głównej mierze zależy od preferencji inwestorów. Niemniej jednak, aby ocenić ewentualne przyszłe ryzyko, należy go zmierzyć. Jest wiele różnych miar służących do jego pomiaru.

W artykule skupiliśmy się nad kwantylowymi miarami zagrożenia Value-at-Risk – VaR oraz Conditional Value-at-Risk – CVaR. Będziemy te miary wyznaczać trzema znanymi metodami. Energia elektryczna jest towarem czasu rzeczywistego, którego się nie magazynuje, co w znacznym stopniu wpływa na kształtowanie się jej cen. Miary najgorszych realizacji spośród możliwych są efektywniejsze w przypadku oszacowania ryzyka na rynku energii niż miary przeciętne. Celem referatu jest wybór takiej spośród metod wyznaczania VaR oraz CVaR, aby najprecyzyjniej oszacować ewentualne przyszłe ryzyko straty na polskim rynku energii. Wyniki badań oparte są na logarytmicznych stopach zwrotu cen zanotowanych na Towarowej Giełdzie Energii oraz Rynku Bilansującym (RB) w okresie od 1 października do końca 2002 r., oraz na symulowanych rozkładach tych stóp zwrotu.