Historical Data in the Context of Risk Prediction

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ABSTRACT

An important element of a successful prediction of the future behavior of financial instruments is a thorough analysis of possible determinants that effect the final estimates of the prognostic models. In the case of *VaR* models, we may include here specified values of significance levels or assumed smoothing constant. Also, an important element is the number of historical observations that should be taken into account in order to estimate the scale of the risk. In the article, therefore, a study of the effectiveness of certain value-at-risk models in the context of historical data had been carried out. Thus, an attempt to assess the impact of the amount of historical data on the effectiveness of the *VaR* indications had been made.

1. Introduction

Assuming that predicting the future bothers many since the dawn of history, it is worth considering the issue of possible factors which in greater or lesser scope have an impact on the effectiveness of forecasting the future states. Determinants of having a significant impact on the accuracy of the forecasts are a vital element in the whole process of scale estimation risk. The lack of respect for them may lead to inaccurate estimates in spite of well-chosen models.

A good method of risk measurement is commonly known as *Value at Risk*. It is a measure, which with in advance assumed probability, indicates on the scale of potential losses within a specific period of time. Thus, this measure gives a direct answer to the issue of the scale of the threats that may take place e.g. the next day. The rest depends only on the investor and the scale of its aversion to risk. However, he gets specific information about the dimension of the possible risks and taking the final investment decision depends only on his personal predispositions, social, cognitive and emotional tendencies.

However, it should be remembered that we are dealing with a wide range of methods for estimating *VaR* both to the concepts i.e., parametric methods, nonparametric or semiparametric and different concepts within the group, such as a GED class model or even GARCH. Also important is the issue of modeling the random interference with the help of specific distributions, like normal distribution or t-Student. Even in a group of simulation methods we are dealing with two types of models such as Monte Carlo simulation and historical simulation which make a great deal of different concepts of value-at-risk estimates.

The purpose of this article was not only the fact of presenting different approaches to the modeling *VaR,* as it has been made in the literature before, but to pay attention to the determinants of the models mentioned above.

In order to present a full examination of the flexibility of value-at-risk the listing companies included in the WIG20 index of the Stock Exchange in Warsaw in the period from January 2010 to December 2012 were taken into consideration which is a period of three years and, therefore, nearly 800 trading days. It seems that such a period of time is sufficient in order to make an objective assessment of the effectiveness of the *VaR* estimates by so called backtesting.

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2. Value-at-Risk – historical background

The major blooming period of *VaR* method is observed in the 1990s of the 20th century. Its history dates back to the mid-1980s. Initially, the use of value-at-risk was associated with the activities of *Bankers Trust* and *JP Morgan*, but it soon became apparent that this method is very useful.

In the 80s a whole range of new assets, whose level of risk was hard to assess, appeared in the financial markets. First of all, because their trade on the open market was limited. Secondly, a lot of hybrid organizations (insurance and investment) emitting pretty new, unknown so far financial instruments, appeared in the market.

Gaining through years the experience in the assessment of the particular type of risk was no longer sufficient. The rate of forming new types of financial instruments exclude the possibility of limiting the specialization in one narrow area of financial markets. It forced the creation of a single tool to measure the risk, which would provide the level of risk of heterogeneous assets in easily comparable units.

The pioneer of the *VaR* method became *JP Morgan*. For several years the method was refining (*VaR* was mainly based on historical observations of specific portfolios of assets, which had to take at least several years of backtesting). In the early 1990s, the *VaR* method was ready. There had been created the method which reported the overall level of risk, regardless of the types of assets in the commonly understood units. The principle of functioning of the *VaR* was simple: if the portfolio of assets brought more profits with less *VaR* risk level, its volume should have been increased. If the particular unit made more profit at the same *VaR* level the involvement in the unit should have been increased. If the broker generated higher profits at the same level of *VaR*, he deserved respectively a larger bonus.

3. Determinants of *VaR* models

One of important elements deciding on the effectiveness of *Value at Risk* models is widely understood variability. To build a reliable *Value at Risk* model, it is important to understand the variability and the behavior of its models. The right choice of the model variability is therefore one of the most important factors determining the efficiency of the chosen *VaR* model. It depends on it whether the model that we take into consideration will not underestimate the risk, or the values it generates, far exceed the legal limits. This issue is a consequential problem and a special attention should be paid to it, as the models presented in this work are based on various methods of determining variability.

Basically, the *VaR* methods can be divided into two groups i.e., simulation methods and parametric ones.
The first of these groups is so characteristic that it does not accept any assumptions about the form of the subject's distribution of the rank, and also the methods of variability output use no equations. Variability index sets a price change corresponding to quantile equal to the required level of confidence. Percentile methods, as they are often used to be called, are preferred by those who believe that the assumption of normality of the distribution is a weak point of the overall *VaR* model.

However, an important drawback of these methods is that they assume that the variability is constant at any given time, and thus these models assign equal weight to each daily return. It is widely accepted, however, such variability in the financial world are not constant, but quite the opposite, almost constantly change. In fact, the financial markets have irregular but often sharp changes in variability which means after the period of low variability there can be observed the period of high one (Best, 2000).

Such an approach implies the need to use some other models, and the explanation of it is the phenomenon of 'the grouping of income from financial assets', based on the fact that the economic information immediately affect the income of the day, and to a lesser extent on the income of the following days i.e., the impact spread in a relatively short period of time. The presence of autocorrelation means that the income from the last period provide more information about the current level of variability than those from the earlier period. It is suggested that in order to obtain the model of variability that accurately measures the current level, it would be advisable to assign a higher weight to the previous income.

So as it takes the second group of models, which can include analytical models, which describe in a different way 'the behavior' of financial instruments in the investment portfolio.

Basically, we can distinguish here the models developed by the group of J.P. Morgan, based on the variability models created with the usage of exponentially weighted moving average – EWMA (Crowder, 1987) and class models GARCH – generalized autoregressive conditional heteroskedastic (Bollersev, 1986), (Bollersev, 1987). EWMA is an important element of *Value at Risk* model known as *RiskMetrics*™. That is an essential subject of further consideration.

The equations to derive mentioned variabilities are described as:

$$\sigma_t^2 = (1-\lambda)r_t^2 + \lambda\sigma_{t-1}^2 \qquad (1)$$

and

$$\sigma_t^2 = \alpha_0 + \alpha_1 \cdot r_{t-1}^2 + \beta_1 \cdot \sigma_{t-1}^2; \alpha_0, \alpha_1, \beta_1 > 0. \qquad (2)$$

While in the EWMA model parameters are easy to estimate, in case of the class models GARCH – there is a variety of strains – and their designation is not always an easy process. Their estimation requires maximizing of the reliability function. Here, the presence of extreme price changes in the rank of data can cause problems for the maximum reliability function – used in this case to calculate parameters – manifested in the lack of convergence.

The major difference between the mentioned EWMA model and the class models GARCH is the fact that the second group of models corresponds even more aggressively to changes in time rank than the EWMA model. Furthermore, interesting and useful feature of GARCH models seems to be the fact that they cover the phenomenon of 'return to the mean'. This is mainly connected with the fact that the value of certain financial assets fluctuates around a long-term value.

Another important fact which should be considered when determining the *VaR* is a number of historical observations that should be taken into account. We should think how far shall we look into the past in order to predict with the greatest accuracy the possible negative effects of market changes. Beyond the significance level, it is therefore the value in a large extent responsible for the *VaR* estimates. There is a need to determine the minimum number of observations that is necessary to estimate the estimator of the standard deviation for daily logarithmic returns of the process of the examined instrument. Using in this respect the relationship developed by *Risk Metrics™*

$$\sigma_t^2 = (1-\lambda)\sum_{j=0}^{n} \lambda^j \cdot r_{t-1-j}^2 \qquad (3)$$

we can attempt to designate the effective number of historical observations.
It is generated in a way that the sum of weights for finite moving average (equal to $1 - \lambda^n$) accounted for a relatively large percentage: $1 - \gamma_{tol}$ from the sum of weights for a theoretical infinite moving average (which is 1), where: $0 < \gamma_{tol} < 1$ – is a sufficiently small tolerance level. We obtain the relationship binding the smoothing constant, the tolerance level and the required number of historical observations:

$$1 - \lambda^n = (1 - \gamma_{tol}), \qquad (4)$$

The equation (4) implies the following formula enabling to determine the required number of historical observations depending on the established tolerance level and adopted the smoothing constant (Jangwoo & Mina, 2001), (Pisula & Pisula, 2001):

$$n = \frac{\ln(\gamma_{tol})}{\ln(\lambda)}, \qquad (5)$$

Therefore, starting from the assumption that the smoothing constant λ adopted by *RiskMetrics*™ for daily data is 0,97 and γ_{tol} is set at the level of 0,01 so $n = 151$ historical observations is the optimal number allowing to generate effectively the value-at-risk. Thus, in this case we need to move back more than six and a half months when it comes to stock listing. It must therefore be admitted that it is quite a lot as far as stepping back in history is concerned.

Figure 1 shows the accurate data in this context depending on the adopted smoothing constant.

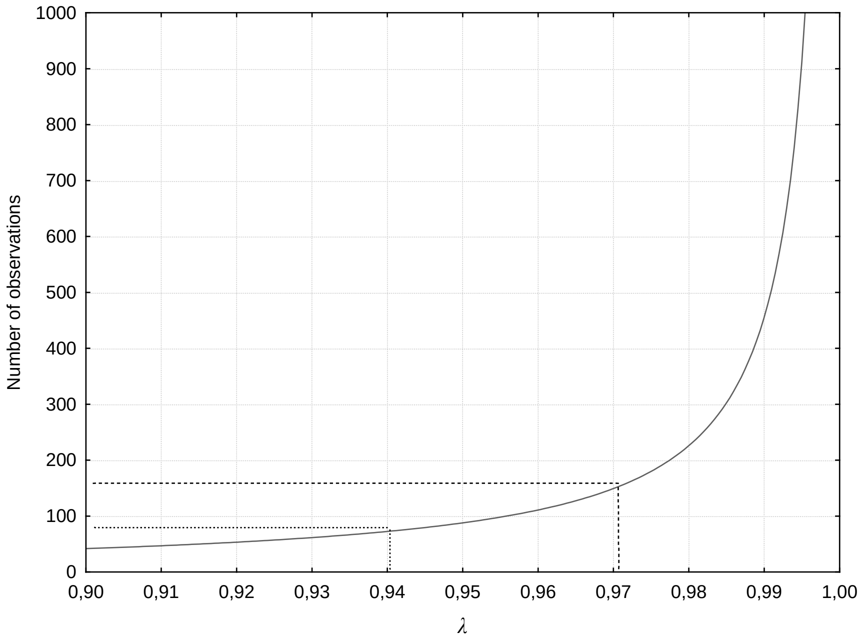

Figure 1. The number of historical observations as the smoothing function λ.
Source: own study based upon RiskGrades™ Technical Document, Second edition, February 2001.

Besides, another important factor determining the degree of *VaR* estimates is the level of significance α, that should be assumed as far as its estimation is concerned. The change in the significance level definitely affect the *Value at Risk*. Increasing the value of α causes the reduction at the level of value-at-risk which is somewhat intuitive. It should be noted that not all the concepts of determining the *VaR* respond equally to changes in the level of significance. There are some methods that are in this respect more or less flexible (Mentel, 2011). However, this is not the study subject of this publication.

4. The form of analytical models

Assuming that the *VaR* methodology is essentially delimited into two subgroups, it is worth quoting the approaches to maximum estimates of potential losses taken into consideration in this publication.

Thus, we are dealing with the concept of historical simulation, in which the actual data is used, which reflects much better the behavior of the market rather than other classical methods. The main advantage of this method is the fact that it is a non-parametric method. This means that on one hand, there are no limitations resulting from the need of adopting the assumptions of normality, on the other hand, estimation of some parameters is avoided (such as mean or standard variation) based on historical data (Jajuga, 2000). Using historical model we must collect a large series of data. The higher its number is, the greater the accuracy. However, very distant data is often out of date, and not as much important as the less distant one. Sometimes gathering the sufficient number of data is simply impossible and the use of this method is then limited.

This method of calculating *VaR* is sensitive to extreme rates of return included in the distribution. As a result, the size of *Value at Risk* changes in a 'stepped' way and the size of risk is often under or overestimated.

Monte Carlo simulation method, in turn, is based on the hypothetical stochastic model that describes the evolution of the price of financial instruments. The essence of the stochastic processes is that it is not possible to predict the value of the process, we can only determine the probability of the given value to be reached. The value of the process is only dependent on time and the previous value of the process.

In the Monte Carlo method a hypothetical model, that describes the mechanism of price formation (or rate of returns) of financial instrument, is assumed. It is often assumed that this process is a geometric Brownian motion. Using as a basis this or other models (model of 'returning to mean' (Risk Metrics Technical Document, 1996), the jump and diffusion model (RiskMetrics Monitor, 1996), etc.), a lot of observations of prices of financial instruments are being generated. In this way, a distribution of the rate of return of the financial instrument is received. Determination of the quantile of this distribution allows directly to determine *VaR*. The process parameters are most frequently estimated on the basis of the past data (Jajuga, 1999).

Considering parametric methods in estimation there had been chosen a several models to compare a few models especially important because of their practical applications, and which had been introduced and successfully used by analysts and financial engineers gathered around the *RiskMetrics™*:

Risk Metrics Drift Model with the random modeled interference with the usage of the normal distributions (Risk Metrics Technical Document, 1996).

In this model it is assumed that logarithmic returns of stock prices are generated according to the following process:

$$r_t = \mu + \sigma_t \cdot \varepsilon_t, \varepsilon_t : N(0,1), \ \tilde{r}_t = \frac{r_t - \mu}{\sigma_t} : N(0,1) \qquad (6)$$

In this model, so called conditional variance for the daily returns of stock prices (in the practical assumption that their average value is zero) is calculated as infinite moving average with exponential weights: $\sigma_t^2 = \sigma^2{}_{t|t-1} = (1-\lambda)\sum_{j=0}^{\infty} \lambda^j \cdot r^2_{t-1-j}$. Approximately for the sufficiently large number of historical observations ($n \to \infty$) this dependence can be written as follows $\sigma_t{}^2 = (1-\lambda)\sum_{j=0}^{n-1} \lambda^j \cdot r^2_{t-1-j}$, and recursively as: $\sigma_t^2 = (1-\lambda) r_{t-1}^2 + \lambda \sigma_{t-1}^2$.

For returns with longer time horizon (T>0) we use (practical for logarithmic returns) scaling of the variance in the length of this horizon (Pisula & Pisula, 2002).

As it was mentioned above, *RiskMetrics*™ uses in their analysis universal smoothing constant λ=0,97 for daily returns. In subsequent calculations there will be used, however, individual smoothing constant calculated separately for each of the analyzed time rank.

VaR boundaries estimated on the basis of the above model (on the assumed level of significance α) for daily time horizon for returns and share prices will be respectively:

$$\mu + \tau_{N(0,1),\alpha/2} \cdot \sigma_t \le r_t \le \mu + \tau_{N(0,1),1-\alpha/2} \cdot \sigma_t \qquad (7)$$

$$P_{t-1} \cdot \exp(\mu + \sigma_t \cdot \tau_{N(0,1),\alpha/2}) \le P_t \le P_{t-1} \cdot \exp(\mu + \tau_{N(0,1),1-\alpha/2} \cdot \sigma_t),$$

where:

$\tau_{N(0,1),\alpha/2}$, $\tau_{N(0,1),1-\alpha/2}$ - the corresponding quantile of a given rank in a normal distribution.

The corresponding model parameters (λ and μ) are determined using the method of maximum reliability.

Model RiskMetrics t-Student with random interferences modeled by t-Student distribution (Risk Metrics Technical Document, 1996) (RiskMetrics Monitor, 1996).

In this model it is assumed that the returns are generated according to the following process:

$$r_t = \mu + \sigma_t \cdot \varepsilon_t, \varepsilon_t : t - Student(0,1,\nu) \qquad (8)$$

$$\tilde{r}_t = \frac{r_t - \mu}{\sigma_t} : t - Student(0,1,\nu)$$

VaR boundaries estimated on the basis of the above model (on the assumed level of significance α) for daily time horizon for the returns and share prices are respectively:

$$\mu + \tau_{t(0,1,\nu),\alpha/2} \cdot \sigma_t \leq r_t \leq \mu + \tau_{t(0,1,\nu),1-\alpha/2} \cdot \sigma_t \tag{9}$$
$$P_{t-1} \cdot \exp(\mu + \sigma_t \cdot \tau_{t(0,1,\nu),\alpha/2}) \leq P_t \leq P_{t-1} \cdot \exp(\mu + \tau_{t(0,1,\nu),1-\alpha/2} \cdot \sigma_t),$$

where:

$\tau_{t(0,1,\nu),\alpha/2}$, $\tau_{t(0,1,\nu),1-\alpha/2}$ - the corresponding quantile of a given rank in t-Student distribution.

Risk Metrics Normal Mixture Model with random interference modeled by a 'mixture' of normal distributions (Risk Metrics Technical Document, 1996) (RiskMetrics Monitor, 1996).

In this model it is assumed that the returns are generated according to the following process which is so called the 'mixture of normal distributions':

$$r_t = \sigma_t \cdot \delta_t \cdot \varepsilon_{1,t} + \sigma_t \cdot (1 - \delta_t) \cdot \varepsilon_{2,t}, \tag{10}$$

where:

$$\varepsilon_{1,t} : N(\mu_1, \sigma_1^{\ 2}); \varepsilon_{2,t} : N(0,1); \delta_t \in \{0,1\}; P(\delta_t = 1) = p; P(\delta_t = 0) = 1 - p.$$

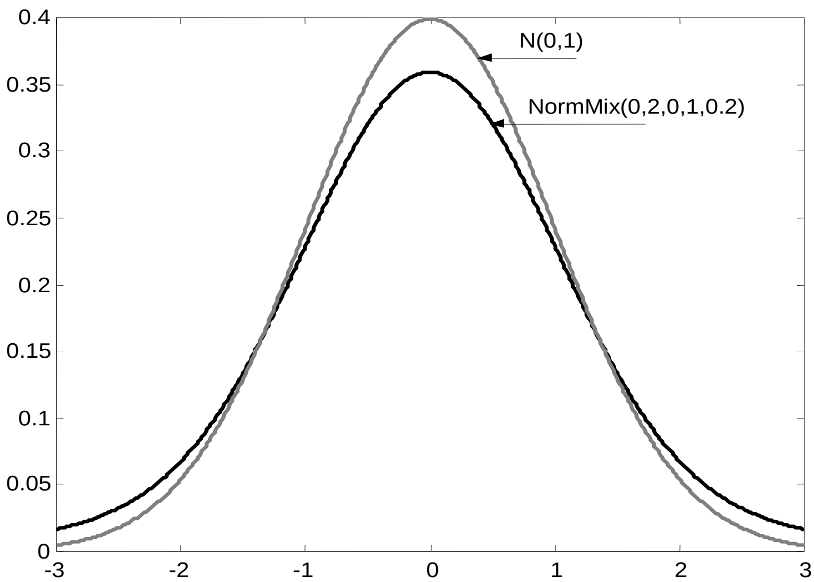

Figure 2. The chart of the density function for a mixture of normal distributions with different values of distribution parameters.

Source: Mentel G., *Value at Risk w warunkach polskiego rynku kapitałowego*, Wydawnictwo CeDeWu, Warszawa 2011.

If $\delta_t = 0$, that occurs with the probability *„1-p"*, to $\tilde{r}_t = \frac{r_t}{\sigma_t} : N(0,1)$ - then the returns are generated as in the classical model of *RiskMetrics*™ (without the drift: μ=0).

If $\delta_t = 1$, and this occurs with the probability „*p*", to $\tilde{r}_t = \dfrac{r_t}{\sigma_t} : N(\mu_1, \sigma_1^2)$ - then the standardized returns are generated according to a normal distribution with the appropriate parameters.

The function of distribution density of standardized returns $\tilde{r}_t = \dfrac{r_t}{\sigma_t}$ for such mixture of normal distributions (see Figure 2) is in the form of:

$$f(x, \mu_1, \sigma_1, 0, 1, p) = \frac{p}{\sqrt{2\pi}\sigma_1} \exp\left(-0.5\left(\frac{x-\mu_1}{\sigma_1}\right)^2\right) + \frac{1-p}{\sqrt{2\pi}} \exp\left(-0.5x^2\right) \tag{11}$$

VaR boundaries estimated on the basis of the above model (on the assumed level of significance α) for daily time horizon will be appropriate for the returns and share prices in the form of:

$$\tau_{NormMix(\mu_1,\sigma_1,0,1,p),\alpha/2} \cdot \sigma_t \le r_t \le \tau_{NormMix(\mu_1,\sigma_1,0,1,p),1-\alpha/2} \cdot \sigma_t \tag{12}$$

$$P_{t-1} \cdot \exp(\sigma_t \cdot \tau_{NormMix(\mu_1,\sigma_1,0,1,p),\alpha/2}) \le P_t \le P_{t-1} \cdot \exp(\tau_{NormMix(\mu_1,\sigma_1,0,1,p),1-\alpha/2} \cdot \sigma_t),$$

where:

$\tau_{NormMix(\mu_1,\sigma_1,0,1,p),\alpha/2}$, $\tau_{NormMix(\mu_1,\sigma_1,0,1,p),1-\alpha/2}$ - the corresponding quantile of a given rank in the assumed mixture of normal distributions.

RiskMetrics GED Model with the random interferences modeled by general error distribution (General Error Distribution – GED) (Risk Metrics Technical Document, 1996) (RiskMetrics Monitor, 1996).
In this model, it is assumed that the returns are generated according to the following process:

$$r_t = \mu + \sigma_t \cdot \varepsilon_t, \varepsilon_t : GED(0,1,\nu), \tilde{r}_t = \frac{r_t - \mu}{\sigma_t} : GED(0,1,\nu) \tag{13}$$

The density function for the general error distribution $GED(\mu, \sigma, \nu)$ with the parameters: location μ, scale σ and shape ν is in the form of:

$$f(x, \mu, \sigma, \nu) = \frac{\nu}{\omega 2^{\left(1+\nu^{-1}\right)} \Gamma\left(\nu^{-1}\right)\sigma} \exp\left(-0.5\left|\frac{x-\mu}{\omega\sigma}\right|^{\nu}\right), \tag{14}$$

where:

$$\omega = \left(2^{-(2/\nu)} \cdot \frac{\Gamma(1/\nu)}{\Gamma(3/\nu)}\right)^{1/2}, \ \Gamma \text{ - gamma function.}$$

GED distribution is often used in practice as it has so called 'fat tails'. This means that the forecasts constructed on the base of GED distribution capture the extreme observations easier (see Figure 3). If the shape parameter $\nu = 2$, then GED distribution is a normal distribution $N(\mu, \sigma)$.

VaR boundaries estimated on the basis of the above model (on the assumed level of significance α) for daily time horizon will be appropriate for the returns and share prices in the form of:

$$\mu + \tau_{GED(0,1,\nu),\alpha/2} \cdot \sigma_t \le r_t \le \mu + \tau_{GED(0,1,\nu),1-\alpha/2} \cdot \sigma_t \tag{15}$$

$$P_{t-1} \cdot \exp(\mu + \sigma_t \cdot \tau_{GED(0,1,\nu),\alpha/2}) \le P_t \le P_{t-1} \cdot \exp(\mu + \tau_{GED(0,1,\nu),1-\alpha/2} \cdot \sigma_t),$$

where:

$\tau_{GED(0,1,\nu),\alpha/2}$, $\tau_{GED(0,1,\nu),1-\alpha/2}$ - the corresponding quantile of the given rank in the GED distribution.

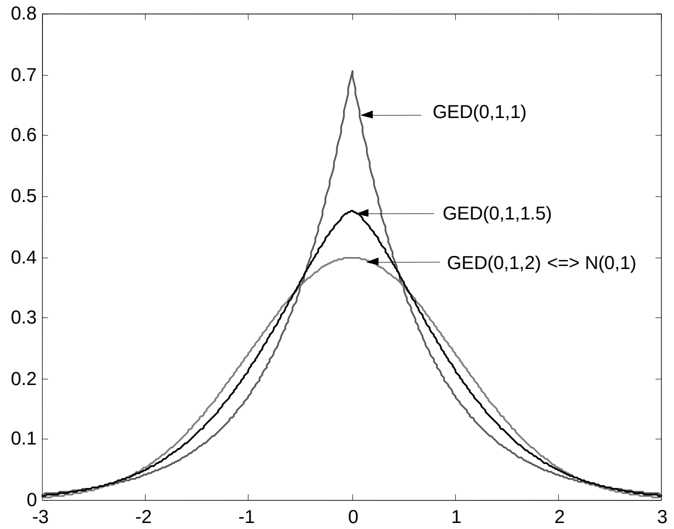

Figure 3. The chart of density function of GED distribution for different parameters.
Source: Pisula T., Pisula J., *Możliwość efektywnego przewidywania ryzyka zmian kursów akcji spółek notowanych na GPW*, Rynek Terminowy nr 17/3/02.

5. The empirical analysis

While assessing the basic estimated value of the *Value at Risk* in the context of the impact of the amount of the historical observations on the effectiveness of *VaR* indications, several levels of historical data were used. The received values of potential losses were determined on the basis of the study from 50 to 200 days back, at intervals of 25 days, which gave seven levels of the past listing values. All calculations were carried out for $\alpha=0.05$, since the *VaR* sensitivity testing on the change of significance levels were carried out in the pages of a separate publication (Mentel, 2011).

All necessary parameters of models taken into consideration for the estimation, were estimated with the usage of maximum reliability method. As to the calculations, they were made at the sample of twenty companies listed on the Warsaw Stock Exchange, as it was mentioned in the introduction, which seems to be a fairly large group of entrants when it comes to carrying out any inferences.

In the studies, the class models GARCH (1,1) were omitted as only for a small group of entrants it was possible to estimate the parameters of the model. The problems concerned the lack of convergence as far as the mentioned above function of maximum reliability is concerned.

Therefore, focusing strictly on the analysis of the received results we have to highlight the fact of significant deviation of *RiskMetrics t-Student* indications where the random interferences were modeled precisely by t-Student distribution (Fig. 4). This is mainly due to the fact that such distribution handles much better in the event of extreme observations, and therefore the key factors are here the 'fat tails'. Similar observations had been noted earlier at the stage of the study of the influence of the significance level on the *VaR* estimates, where in the case of analysis it was possible to use the class model GARCH (Mentel, 2011). There, the general guidelines for the discussed distribution were significantly better than for the random interferences modeled by normal distribution. It should be emphasized, however, that the remaining group of methods in case of individual entrants is also doing well. Averaging the results of the estimates for the entire study sample we get the results that can be observed in the mentioned Figure 4. In addition, it can be said that the simulation models are doing the worst.

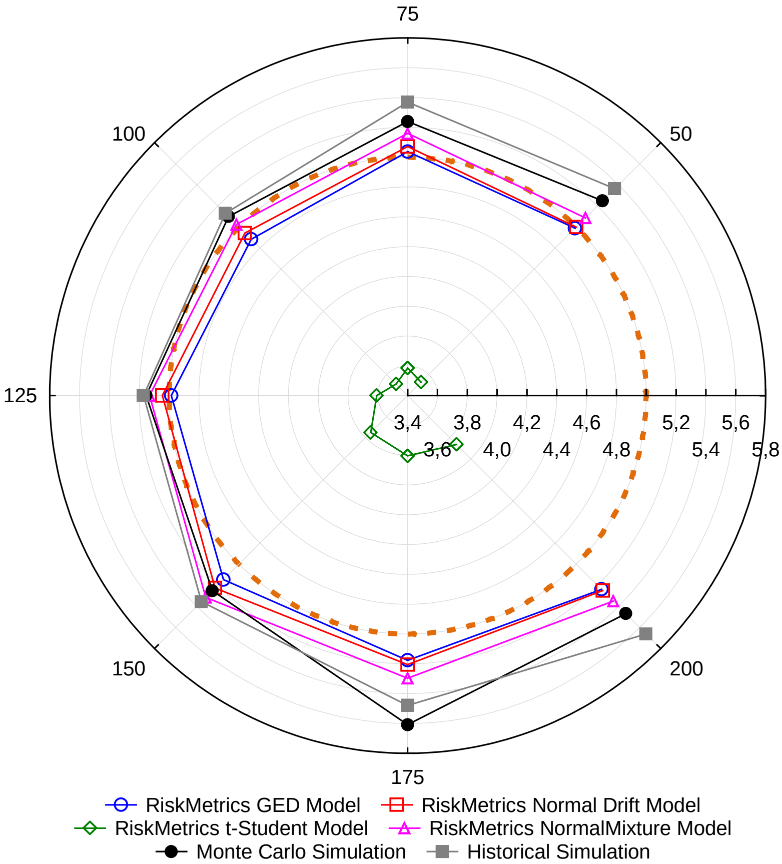

Figure 4. The average value of the percentage of exceedances beyond the *VaR* values for the different number of historical observations taken to their estimation (α=0,05).
Source: own study.

Table 1. The values of the smoothing constant λ in the section of models.

	Risk Metrics GED	*Risk Metrics Normal*	*RiskMetrics t-Student*	*Risk Metrics Normal Mixture*
AssecoPol	1,002090	0,954389	0,944217	0,918641
Bank Handlowy	0,948311	0,954373	0,946680	0,930069
Bogdanka	1,001220	1,002350	0,963477	0,851728
Boryszew	0,994859	0,990841	0,782848	0,736877
BRE Bank	0,922980	0,914552	0,927885	0,900436
GTC	0,967670	0,978482	0,963360	0,957721
Jastrzębska Spółka Węglowa	0,925009	0,927996	0,919487	0,866749
Kernel	1,004840	0,965543	0,944696	0,924287
KGHM	0,940196	1,001530	0,939152	0,935228
Lotos	0,956758	0,955977	0,957096	0,948923
Pekao	0,944258	0,944536	0,945461	0,940240
PGE	0,923163	0,926529	0,920565	0,907382
PGNiG	0,944867	0,935948	0,945786	0,907585
PKN Orlen	0,955564	0,954468	0,954791	0,935015
PKO BP*	0,940204	0,937841	0,940392	
PZU	0,955083	0,951695	0,958898	0,927072
Synthos	0,957255	0,938880	0,959520	0,894264
Tauron Polska Energia	0,914141	0,935243	0,885797	0,839022
TP S.A.*	0,986180	1,001980	0,980830	
TVN	0,952498	0,938435	0,961627	0,931236
Mean	**0,956857**	**0,955579**	**0,937128**	**0,902915**

* In the case of PKO BP and TP S.A. it was impossible to estimate the parameters for *RiskMetrics NormalMixture* model.
Source: own study.

Departing from the analysis of the methods used, it should be noted that the best results were obtained for a hundred of historical observations taken for analysis. Slightly different indications were also obtained for n=125 days. Thereby, increasing the amount of historical observations beyond the threshold of 125 days entails only the deterioration of the general indications. Excluding from the analysis the simulation methods, equally good results were obtained for 50 days. For some entrants for such value of past data the results were better than in the case of withdrawal of 100 days (Fig. 5).

It should be remembered that all the calculations were based on individual smoothing constant and not as it is rigidly recommended by *RiskMetrics™*. The values of λ are presented in the Table 1.

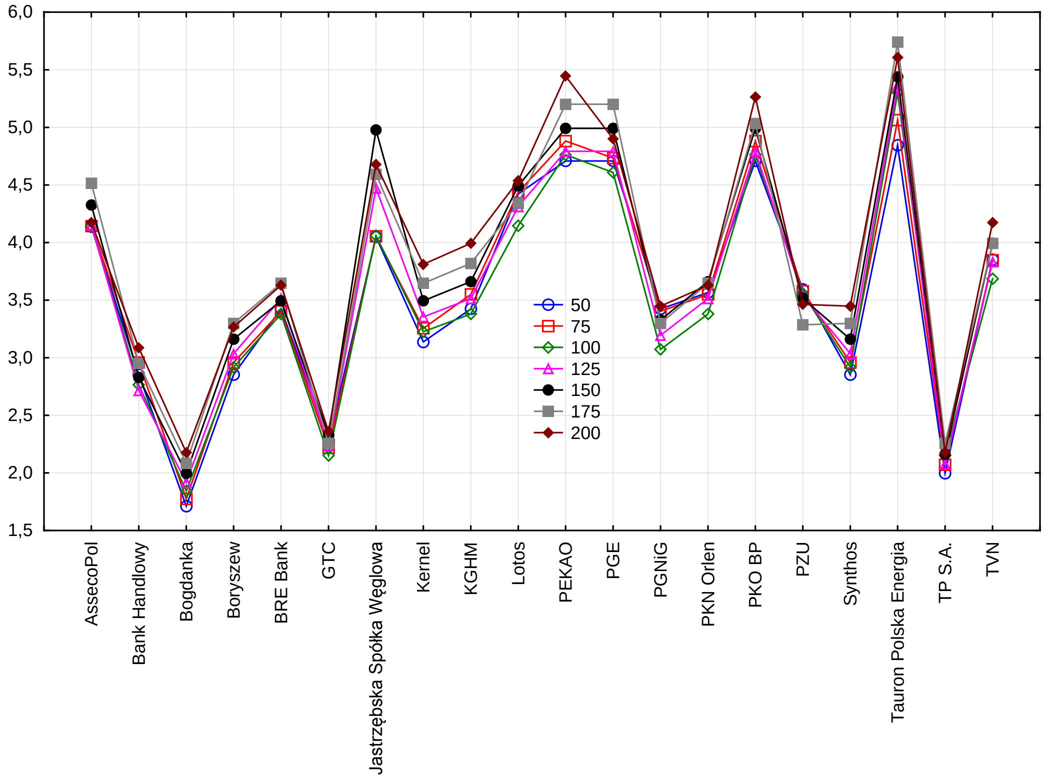

Figure 5. The value of the percentage of exceedances beyond the *VaR* values for *RiskMetris t-Student* model in the section of analyzed advantages (α=0,05).
Source: own study.

6. Conclusions

Analyzing the *Value at Risk,* we should pursue to the fullest possible knowledge of the method itself, but also keep in mind the need to explore the use of such a method. The lack of understanding of the basic structural building of *VaR* model is one of the main reasons for the possible negative results of its use. This state of affairs is the major drawback of this method. Therefore, all the work which aim to explore its secrets, by analyzing the factors that have a direct influence on it are becoming extremely important.

The essential element of methodology is so called the distribution model, which should faithfully reflect the behavior of the market, causing thereby that the *VaR* is flexible and responsive to changing market conditions. It is worth emphasizing that as far as the market is concerned, the most interesting things happen at the end of the distributions of variables which is contrary to the common assumption of normality. The biggest profits and losses do not produce the normal days but the extreme ones (Taleb, 2007). Hence, better results are obtained when the random interferences are modeled even by the distribution of *t-Student*.

As far as the significance levels are concerned, the most frequently is used the value of 0,05 or recommended by the Basel Committee on Banking Supervision 0,01. On the basis of personal experience, it seems that the use of that first gives in this case the best results.

In contrast, taking into account the number of historical observations that must be considered to have a good estimate of the size of potential losses, it seems that the relationship developed by *RiskMetrics™* gives the good basics. For daily data, looking into the past beyond the level of a hundred days seems to make no sense. Thus, a wider historical *VaR* is not a panacea for the ills of valuation methods. Artificial increasing of historical data does not translate into an improvement in the efficiency of the method itself but quite the opposite. It is therefore confirmed that the most important things while predicting the future are the recent events and the process of reversing the past entails the phenomenon of ageing information. The above mentioned process runs exponentially. In addition, we need to be skeptical in the case of all the events from the past. Even if they are important for what is soon likely to happen, it will rather not repeat with the same force as it had already taken place. Due to the historicity of the market processes, nothing happens twice as far as markets are concerned, or at least it does not happen in the same way. Thus, so called *stress testing,* used as a supplement to the *VaR* in order to protect against the extreme situations on the market, is not a panacea to improve any shortcomings of the *Value at Risk* methodology.

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