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VaR CALCULATOR

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Abstract- This study concerns the characteristics of loss risk analysis software developed by the Authors. The *VaR Calculator* significantly improves estimation of value-at-risk along its determinants such as level of confidence, constant smoothing factor or the number of past observations. Its additional benefit consists in compiling several different methods of determining value-at-risk in one programme and making the computational procedures more efficient. Therefore, the calculator described provides a free, constantly updated option for predicting negative market changes and thus reducing risk.

Keywords- value-at-risk, modelling, risk, prediction, software

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Introduction

Very often time series methods are used for assessment of stock investment risk. Stock exchange investment risk and especially the risk related to investing in securities such as stocks of public companies, results of course from variation of their prices. This is why proper estimation of predicted variability is very important for risk assessment.

In addition, a stock exchange investor, often investing a lot of money in the companies in their portfolio, is interested in knowing the maximum risk of loss as precisely as possible. This risk is often expressed in terms of maximal possible loss the investor can incur to their investment portfolio value in the worst scenario assumed.

This is the basis of a very popular method of financial market risk assessment, estimating the so called value at risk (*VaR*).

The method involves estimation of maximal potential portfolio value loss within the assumed time horizon (e.g. a day, a week), so that the probability that the losses will be even larger is very small (equal to the level of confidence assumed).

Despite current widespread use of VaR, it is difficult to find a tool enabling automation of its estimation. There are programmes allowing Value at Risk to be calculated, but they do not include the wide range of its various concepts – they are rather additions to other statistical packets – or their purchase is quite expensive for an average user (investor).

To meet the considerations described above, the goal was set to automate the process of value-at-risk estimation in a single packet, called VaR Calculator by the authors.

In accordance with the distinctions commonly used in this field, the proposed calculator includes two kinds of VaR estimation methods: the simulation methods (historical simulation and Monte Carlo simulation) and analytical methods (based on various models describing behaviour of financial instruments in an investment portfolio).

VaR History

The need for the programme arose from the Value at Risk (VaR) methodology. It is a quite new concept, first introduced by some international financial institutions in late 80s. Since then, VaR popularity has dramatically increased. Creation of the RiskMetrics™ system by J.P. Morgan in October 1994 was a significant step [1]. *VaR* gained popularity also among companies and institutional investors. The new methodology was further proliferated due to publications such as this by Jorion [2], comprehensively studying VaR considerations, as well as creation of computer systems enabling implementation of the methodology.

The new method attracted attention of supervising institutions as well. In January 1996, the Basel Committee on Banking Supervision amended its capital requirements standards dependent on market risks incurred (*Amendment of the Capital Accord to Incorporate Market Risk*), determining the rules of taking market risks related to changes in interest rates, exchange rates and commodity prices into account by banks, where for the first time the banks were allowed to estimate those risks using internal VaR models. In August of this year, Europe was followed by the United States, where the Federal Reserve Bank (Fed) issued *Risk-Based Capital Standards: Market Risk*, modelled upon the above mentioned Basel Committee amendment.

Both publications determined the standards in accordance to which the banks were to calculate VaR on their own. Also, in 1993 a European Union directive on capital standards came into force, allowing

Value at Risk to be used as a means of calculating risk for currency positions.

Simulation Models

In the *historical simulation* method, VaR is estimated using real data, which is why it reflects real market behaviour better than other classical methods. The main advantage of this method is its non-parametric character. It means that, on one hand, there are no constraints stemming from normality assumption, and on the other hand some parameters (such as average or standard deviation) are not estimated based on historical data [3].

If there are "thick tails" in the real price distribution, the historical simulation method gives a more credible VaR level. Another benefit of historical simulation is that it is easier to estimate than the other methods.

The historical approach is a very intuitive method of estimating Value at Risk. It is determined based on historical returns of investment of a given instrument (or portfolio) and their empirical distribution. It is important to calculate returns for the same period as VaR (if the investment horizon is one day, returns should be calculated daily).

An interesting approach is to generate VaR based on the so called *profit and loss (P&L)*, implemented in VaR Calculator in addition to prices and returns. Such a solution is recommended by the *RiskMetrics*™ group, with Value at Risk calculated based on the profit and loss scenarios determined [4]. In this approach, potential asset prices in the *t* period are tentatively calculated

$$P_t = P_0 \cdot e^{r\sqrt{t}} \qquad (1)$$

where:

P_t - asset price in the period *t*,

P_0 - asset price in the initial period,

r - pre-determined returns rate,

t - time horizon for which VaR is determined,

and then the differences of prices P_0 and scenarios P_t are generated. The generated differences are ordered and then the percentile of the required confidence level is determined – this is how VaR is obtained.

When the historical model is utilised, a large data series needs to be gathered. The more data are collected, the higher precision. However, very distant data are often inapplicable to current circumstances and not as significant as those less distant. Sometimes it is impossible to collect enough data and the applicability of this method is limited.

This method of VaR computation is sensitive to extreme rates of returns included in the distribution. This is why value at risk changes by steps and the risk is often underestimated or overestimated.

The *Monte Carlo simulation* method is based on a hypothetical stochastic model, describing financial instrument price changes. The stochastic processes are characterised by impossibility of predicting process values – only probability of obtaining a given value can be determined. Process value depends only on time and the previous process value.

In the Monte Carlo method a hypothetical model describing the mechanism determining the prices (or returns) of financial instruments is assumed. This process is often assumed to be a geometrical Brownian motion. Using this model or other models (mean reversion model, jump-diffusion model etc.) as a basis, many observations of financial instrument prices are generated. Thus, a returns rate distribution for a financial instrument is obtained. Determining the quantile of this distribution enables direct determination of VaR. The process parameters are typically estimated based on past data [5].

To determine the predicted variance of returns on stock prices, the relationship used by *RiskMetrics*™ in its classical models can be utilised:

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

Estimation of variance of returns on stock prices at time *t* obtained in accordance with the formula above is a weighted arithmetic mean (with weights 1-*l* and *l*) for returns on stock prices at the time *t* squared and the previous estimation of returns at the time *t-1* [4].

Analytical Methods

There are many analytical models describing fluctuations of financial instruments in time. The software developed enables comparison of several concepts, very important due to their practical applications. Most of these models have been introduced and successfully utilised by analysts and financial engineers associated with *RiskMetrics*™. In addition, for comparison, other models based on generalised autoregressive conditional variance processes (*GARCH(1,1) type*), as well as so-called mean reversion models, also successfully used in many financial engineering problems, are provided [6].

RiskMetrics Drift Model with random disturbances modelled using a normal distribution [1,7].

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

$$\mathrm{r_t} = \mu + \sigma_\mathrm{t} \cdot \varepsilon_\mathrm{t}, \varepsilon_\mathrm{t} : \mathrm{N}(0,1),\ \tilde{r}_t = \frac{r_t - \mu}{\sigma_t} : N(0,1) \qquad (3)$$

In this model the so-called conditional variance for daily returns on stock prices (practically assumed to average to zero) is calculated as an infinite moving average with exponential weights:

$$\sigma_t^2 = \sigma^2{}_{t|t-1} = (1-\lambda)\sum_{j=0}^{\infty} \lambda^j \cdot r^2_{t-1-j}$$

In approximation for a sufficiently large number of historical observations ($n \to \infty$), we can write this relationship as follows:

$$\sigma_t{}^2 = (1-\lambda)\sum_{j=0}^{n-1} \lambda^j \cdot r^2_{t-1-j}$$

,

or recursively as: $\sigma_t^2 = (1-\lambda) r_{t-1}^2 + \lambda \sigma_{t-1}^2$

For returns with longer time horizons (T>0) variance scaling according to horizon length (practical for logarithmic returns) is used [8].

VaRe estimated based on the model above (at the assumed confidence level a) for daily time horizon for returns and stock prices, respectively, will be in the range:

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

$$P_{t-1} \cdot \exp(\mu + \sigma_t \cdot \tau_{N(0,1),\alpha/2}) \le P_t \le P_{t-1} \cdot \exp(\mu + \tau_{N(0,1),1-\alpha/2} \cdot \sigma_t) \qquad (4)$$

where: $\tau_{\mathrm{N}(0,1),\alpha/2}$, $\tau_{N(0,1),1-\alpha/2}$ - applicable quantiles of a given rank in normal distribution.

Correct model parameters (l and m) will be determined using the maximum likelihood method.

Model RiskMetrics GED with random disturbances modelled with the General Error Distribution – GED [1,7].

In this model it is assumed that returns are generated in accordance with the following process:

$$r_t = \mu + \sigma_t \cdot \varepsilon_t, \varepsilon_t : GED(0,1,v), \quad \widetilde{r_t} = \frac{r_t - \mu}{\sigma_t} : GED(0,1,\nu) \quad (5)$$

Density function for the general error distribution *GED* (μ,σ,v) with parameters: position μ, scale σ and shape *v* has the form:

$$f(x,\mu,\sigma,\nu) = \frac{\nu}{\omega 2^{\left(1+\nu^{-1}\right)}\Gamma\left(\nu^{-1}\right)\sigma}\exp\left(-0.5\left|\frac{x-\mu}{\omega\sigma}\right|^{\nu}\right) \quad (6)$$

where:

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

GED is often used in practice, as it has so called thick tails. It means that the predictions based on GED are more sensitive to extreme observations. If the shape parameter *v*=2, GED is a normal distribution *N(μ,σ)*.

The *VaR* range estimated based on the model above (at the assumed confidence level a) for daily time horizon, respectively for returns and stock prices, will have the form:

$$\mu + \tau_{GED(0,1,\nu),\alpha/2}\cdot\sigma_t \le r_t \le \mu + \tau_{GED(0,1,\nu),1-\alpha/2}\cdot\sigma_t$$
$$P_{t-1}\cdot\exp(\mu + \sigma_t\cdot\tau_{GED(0,1,\nu),\alpha/2}) \le P_t \le P_{t-1}\cdot\exp(\mu + \tau_{GED(0,1,\nu),1-\alpha/2}\cdot\sigma_t) \quad (7)$$

where: $\tau_{GED(0,1,\nu),\alpha/2}$, $\tau_{GED(0,1,\nu),1-\alpha/2}$ respectively quantiles of the given rank in GED.

Correct model parameters (*l,m,n*) are determined as before, using the maximum likelihood method.

Model RiskMetrics NormalMixture with random disturbances modelled using a mixture of normal distributions [1,7].

In this model it is assumed that the returns are generated in accordance with the following process, the so-called random distribution mixture:

$$r_t = \sigma_t\cdot\delta_t\cdot\varepsilon_{1,t} + \sigma_t\cdot(1-\delta_t)\cdot\varepsilon_{2,t} \quad (8)$$

where:

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

If δ_t=0, which occurs with the probability *1-p*, $\widetilde{r_t} = \frac{r_t}{\sigma_t} : N(0,1)$ - the returns are generated like in the classical *RiskMetrics*™ model (without a drift: m=0).

If δ_t=1, which occurs with the probability *p*, $\widetilde{r_t} = \frac{r_t}{\sigma_t} : N(\mu_1,\sigma_1^2)$- standardised returns are generated in accordance with normal distribution with the applicable parameters.

Distribution density function of the standardised returns $\widetilde{r_t} = \frac{r_t}{\sigma_t}$ for such a mixture of normal distributions has the form:

$$f(x,\mu_1,\sigma_1,0,1,p) = \frac{p}{\sqrt{2\pi}\sigma_1}\exp\left(-0.5\left(\frac{x-\mu_1}{\sigma_1}\right)^2\right) + \frac{1-p}{\sqrt{2\pi}}\exp\left(-0.5x^2\right) \quad (9)$$

VaR boundaries estimated based on the model above (at the assumed confidence level a) for daily time horizon, respectively for returns and stock prices, will have the form:

$$\tau_{NormMix(\mu_1,\sigma_1,0,1,p),\alpha/2}\cdot\sigma_t \le r_t \le \tau_{NormMix(\mu_1,\sigma_1,0,1,p),1-\alpha/2}\cdot\sigma_t$$
$$P_{t-1}\cdot\exp(\sigma_t\cdot\tau_{NormMix(\mu_1,\sigma_1,0,1,p),\alpha/2}) \le P_t \le P_{t-1}\cdot\exp(\tau_{NormMix(\mu_1,\sigma_1,0,1,p),1-\alpha/2}\cdot\sigma_t) \quad (10)$$

where

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

Model parameters (*l,m1,s1,p*) will be determined like in the previous models, using the maximum likelihood method.

Model RiskMetrics t-Student with random disturbances modelled using the t-Student distribution [1,7].

In this model it is assumed that returns are generated in accordance with the following process:

$$r_t = \mu + \sigma_t\cdot\varepsilon_t, \varepsilon_t : t-Student(0,1,\nu) \quad (11)$$

VaR boundaries estimated based on the above model (at the assumed confidence level a) for a daily time horizon, respectively for returns and stock prices, have the form:

$$\mu + \tau_{t(0,1,\nu),\alpha/2}\cdot\sigma_t \le r_t \le \mu + \tau_{t(0,1,\nu),1-\alpha/2}\cdot\sigma_t$$
$$P_{t-1}\cdot\exp(\mu + \sigma_t\cdot\tau_{t(0,1,\nu),\alpha/2}) \le P_t \le P_{t-1}\cdot\exp(\mu + \tau_{t(0,1,\nu),1-\alpha/2}\cdot\sigma_t) \quad (12)$$

where: $\tau_{t(0,1,\nu),\alpha/2}$, $\tau_{t(0,1,\nu),1-\alpha/2}$ proper quantiles of a given rank in t-Student distribution.

Model parameters (*l,m,n*) are determined like in the previous models, using the maximum likelihood method.

Models GARCH(1,1) Normal and *GARCH(1,1) t-Student* with random disturbances modelled with normal and t-Student distributions [9-11].

As an alternative to models proposed by *RiskMetrics*™, other practically significant models will be used, e.g. the *GARCH(1,1)* model, fundamentally distinct due to a different (regressive) approach to estimating conditional variance for returns on stock prices:

$$\sigma_t^2 = \alpha_0 + \alpha_1\cdot r_{t-1}^2 + \beta_1\cdot\sigma_{t-1}^2; \alpha_0,\alpha_1,\beta_1 > 0 \quad (13)$$

In these models returns are generated in accordance with the following processes:

$$r_t = \mu + \sigma_t\cdot\varepsilon_t, \varepsilon_t : N(0,1) \quad \widetilde{r_t} = \frac{r_t - \mu}{\sigma_t} : N(0,1) \quad (14)$$
$$r_t = \mu + \sigma_t\cdot\varepsilon_t, \varepsilon_t : t-Student(0,1,\nu)$$
$$\widetilde{r_t} = \frac{r_t - \mu}{\sigma_t} : t-Student(0,1,\nu) \quad (15)$$

VaR range estimated based on those models (at the assumed level of confidence a) is determined the same as in the models *RiskMetrics Drift* and *Model RiskMetrics t-Student*, taking into account the formula (9).

Model Mean Reversion RiskMetrics Normal with random disturbances modelled using normal distribution and conditional variance modelled as in the models *RiskMetrics*™ [1,7].

As an alternative to the previous models proposed by *RiskMetrics*™ and the *GARCH(1,1)* type models, *Mean Reversion* models will also be used. They use a so-called reversion process of the form:

$$r_t = k \cdot \left(p_{\acute{s}r} - \ln(P_{t-1})\right) + \sigma_t \cdot \varepsilon_t, \varepsilon_t : N(0,1) \qquad (16)$$

where:

$p_{śr}$: average (mean) value of stock price logarithms $\ln(P_t)$,

$k \in [0,1]$: reversion parameter, while conditional variance σ_t^2 is est mated like in the *RiskMetrics*™ and *GARCH(1,1)* models.

The parameter *k* plays an important role in this process; when k=0, there is no reversion (the returns are generated like in the model *RiskMetrics Drift*, only without the drift, m=0). If however k=1, a complete reversion to mean occurs $\ln(P_t) = p_{śr} + \sigma_t \cdot \varepsilon_t, \varepsilon_t : N(0,1)$ natural logarithms of stock prices oscillate around their mean [6].

VaR boundaries estimated based on those models (at the assumed confidence level a) are calculated in the following way:

$$\begin{aligned} & k \cdot (p_{śr} - \ln(P_{t-1})) + \tau_{N(0,1),\alpha/2} \cdot \sigma_t \le r_t \le \\ & \qquad k \cdot (p_{śr} - \ln(P_{t-1})) + \tau_{N(0,1),1-\alpha/2} \cdot \sigma_t \\ & P_{t-1} \cdot \exp[k \cdot (p_{śr} - \ln(P_{t-1})) + \tau_{N(0,1),\alpha/2} \cdot \sigma_t] \le \\ & \qquad P_t \le \\ & \qquad P_{t-1} \cdot \exp[k \cdot (p_{śr} - \ln(P_{t-1})) + \tau_{N(0,1),1-\alpha/2} \cdot \sigma_t] \end{aligned} \qquad (17)$$

The parameter $p_{śr}$ will be determined with the arithmetic mean estimator, k – using the linear regression method, and the parameter l - using the maximum likelihood method.

Model Random Walk with random disturbances modelled with normal distribution.

In this case the returns are generated with the following relationship:

$$r_t = \mu + \sigma \cdot \varepsilon_t, \varepsilon_t : N(0,1) \qquad (18)$$

While *Value at Risk* for returns and stock prices is determined respectively:

$$\begin{aligned} & \mu + \tau_{N(0,1),\alpha/2} \cdot \sigma \le r_t \le \mu + \tau_{N(0,1),1-\alpha/2} \cdot \sigma \\ & P_{t-1} \cdot \exp(\mu + \sigma \cdot \tau_{N(0,1),\alpha/2}) \le \\ & \qquad P_t \le \\ & \qquad P_{t-1} \cdot \exp(\mu + \tau_{N(0,1),1-\alpha/2} \cdot \sigma) \end{aligned} \qquad (19)$$

where: $\tau_{N(0,1),\alpha/2}$, $\tau_{N(0,1),1-\alpha/2}$ respectively, quantiles of a given rank in normal distribution.

Constant variance in time is an important feature of this model.

In all the models we can also use the least squares method, utilising deviation of squares of predicted variance σ_t^2 from actual values of squared returns r_t^2 as an optimisation criterion. The other parameters, related only to random disturbances distribution, can be determined like previously, using the least squares method. Due to such approach, for some models the number of parameters that need to be estimated using the least squares method is greatly reduced and estimation precision [6].

VaR calculator

Computer software market lacks tools that would include a number of different methods for estimating risk, using a number of different models, and if such tools exist, they are expensive, and this means the scientists often cannot afford to buy them. These limitations were the reason why the authors of this study decided to create free software – the *VaR calculator*[3], enabling risk analysis taking into account many concepts. The software is based on *STATISTICA 10* libraries by StatSoft ®, including many different functions, which allows focus on implementation of a specific risk-related problem, not on e.g. coding the t-Student distribution used by a given model.

STATISTICA 10 programme libraries were chosen also because it is one of the most popular programmes owned by scientific institutions. If one does not have a licence for *STATISTICA 10*, its trial version[4] is available at the producer's website.

The programme *VaR calculator* is under constant development, new models are added and computation speed is optimised. Currently the programme is able to calculate risk for the models described above:

RM (ind)
- GED
- NormalMix
- Drift Normal
- T-Student

GARCH(1,1)
- Normal
- T-student

Other
- Random Walk (RW).

After installing the programme with the installer downloaded from http://prz.edu.pl/~jacekb/software/freeware/VaR/ , at each launch it will check the server for a newer version and propose automatic update.

After launching *VaR calculator*, you need first to load [Fig-1] a previously prepared (in *STATISTICA*) price chart file [Fig-2], which can only include a single column.

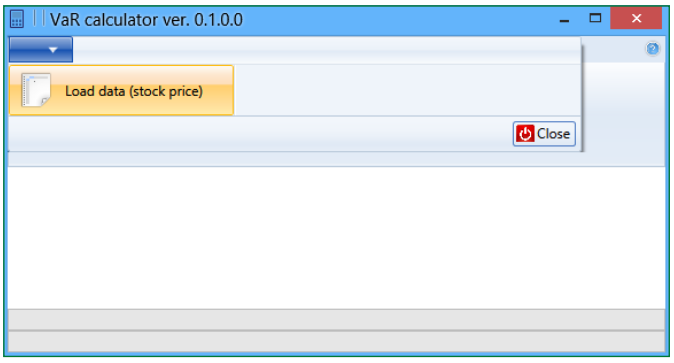

Fig. 1- *VaR calculator:* Load data.

After data are loaded into the programme, a calculation model menu will start, as in [Fig-3]. After choosing one of calculation models, a parameter file choice window will appear (files are in the *STA-*

TISTICA format). The data in parameter file for the model must have the specified parameter order, which is why file examples for each model are provided with the programme [Fig-4].

	1 Kurs AssecoPL
01/04/2010	63,15
01/05/2010	63,10
01/06/2010	63,00
01/07/2010	61,25
01/08/2010	60,15
01/11/2010	60,30
01/12/2010	58,80
01/13/2010	59,00
01/14/2010	59,20
01/15/2010	59,25
01/18/2010	60,65
01/19/2010	60,20

Fig. 2- An example of data (price chart) for *VaR calculator*.

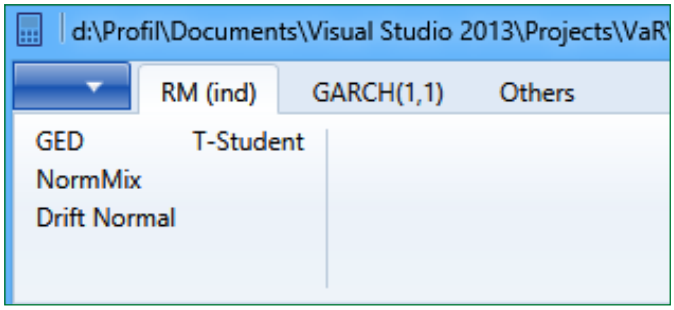

Fig. 3- Model menu of *VaR calculator.*

One of the objectives of the VaR calculator was comfortable and fast data analysis. The first version of the programme, as most tools of this kind, allowed the user to manually enter the parameters for the selected model. By using parameter files, there is no need to type model parameters anew every time, and most importantly, the user can prepare multiple records at once with parameters [Fig-5] e.g. to analyse the impact of a step change in one of them on the risk.

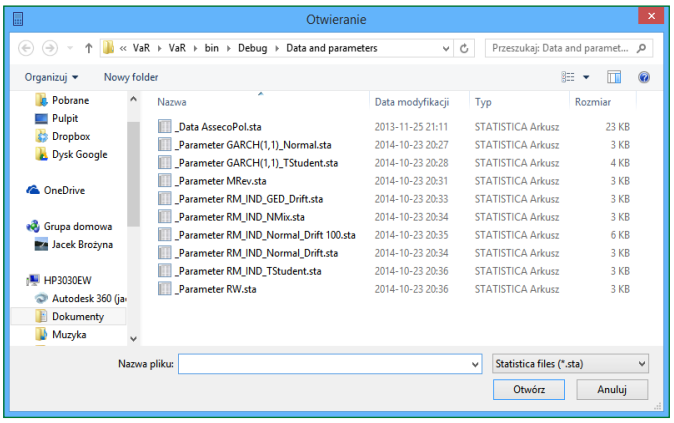

Fig. 4- Parameter choice window / a list of model parameter file examples.

	1 Number of historical observations N	2 Significance level Alpha	3 Drift parameter Mi	4 Decay factor Lambda
1	150	0,1	0,0000280000	0,925234
2	150	0,1	0,0003300000	0,961461
3	150	0,1	0,0013300000	0,961681
4	150	0,1	-0,0008840000	0,979201
5	150	0,1	0,0006720000	0,972276
6	150	0,1	0,0004740000	0,944686
7	150	0,1	-0,0001720000	0,913226

Fig. 5- An example of a parameter file for the RM(ind) Normal Drift model.

The general results of calculations are presented directly in the programme window [Fig-6] and at the same time saved to the system desktop, in the folder *VaR results*, with model name and the suffix - *results* as file name. In addition to the general results, in the "VaR results" folder, detailed calculation results are saved for each parameter record of a given model. The files with detailed results have file names identical as the main file name, but they include record number from the parameter file instead of the – *results* suffix [Fig-7]. Information on the names of the files with detailed results is also visible in the programme window at the end of each parameter record. Such a way of organising result recording enables many different calculations and their later analysis without starting the programme again.

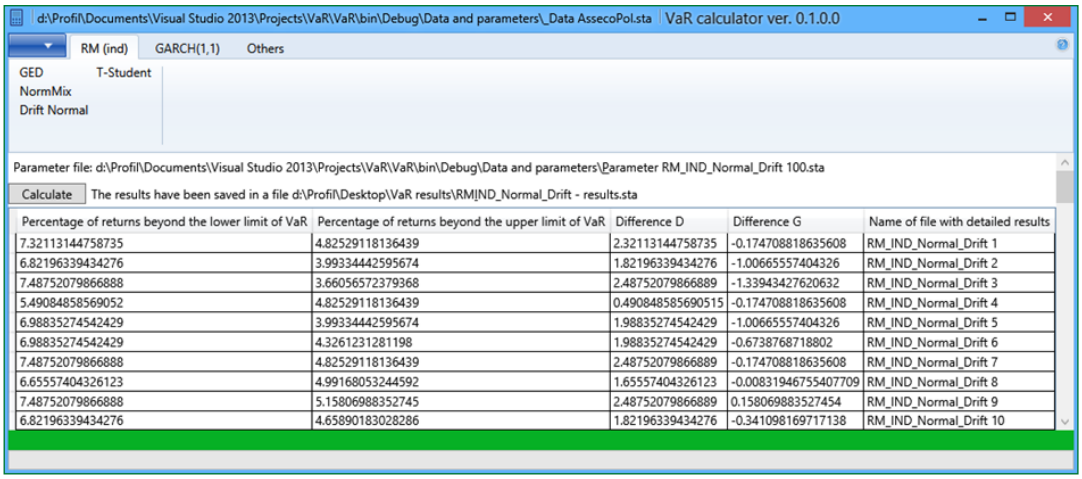

Fig. 6- Calculation results in the programme VaR calculator.

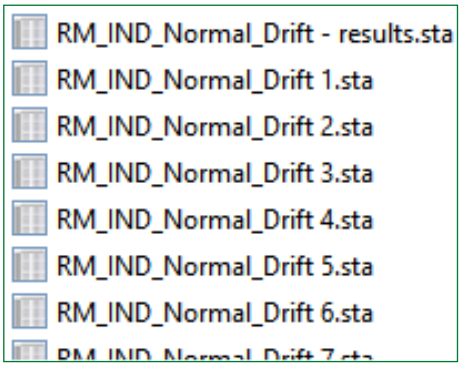

Fig. 7- Examples of files saved by the *VaR calculator* into the *VaR results* folder.

Detailed results include significant intermediate calculations for each model, e.g. for the RM (ind) Normal Drift model:

- VaRD_R_RM_Normal_Drift : lower bound of confidence level for returns rates (*VaR*),
- VaRG_R_RM_Normal_Drift : upper bound of confidence level for returns rates,
- VaRD_Kurs_RM_Normal_Drift : lower bound of confidence level for prices (*VaR*),
- VaRG_Kurs_RM_Normal_Drift : upper bound of confidence level for prices,
- VaRD_ZS1_RM_Normal_Drift : lower bound of confidence level for profits/losses (*VaR*),
- VaRG_ZS1_RM_Normal_Drift : upper bound of confidence level for profits/losses.

The programme *VaR calculator* was supposed not only to be functional, but also to process the data in an efficient manner. This goal has been achieved through use of parallel computing using multithreading processors, enabling for example calculations for several hundred variants of the model parameters and generating detailed results within seconds.

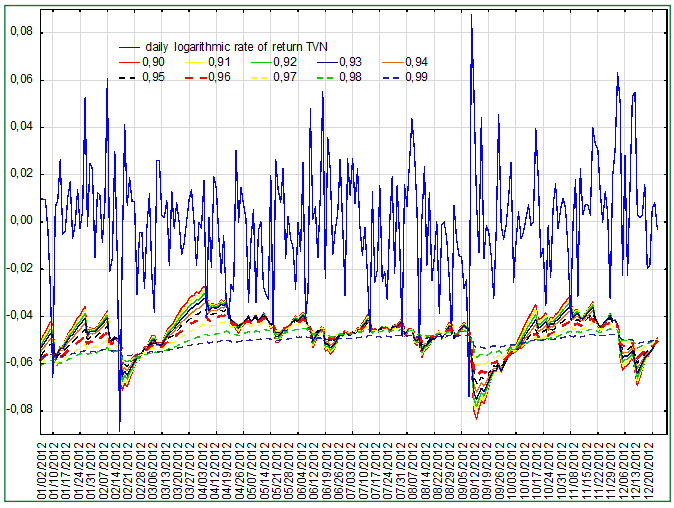

Fig. 8- Value at Risk results for the company TVN in the year 2012, determined using the method RiskMetrics t-Student for various levels of l. Source: Mentel & Brożyna [12]

An example of usage of one of the first versions of the *VaR calculator* can be found in the paper *Decay factor as a determinant of forecasting models* [12], where based on the companies included in 2013 in the WIG20 index the influence of l constant smoothing factor on VaR estimation effectiveness in the context of variability modelling using an exponentially exponentially weighted moving average, or EWMA – an example for the TVN company has been shown at [Fig-8].

Conclusions

Apart from the very essence of the Value at Risk methodology, known by the experts in this field to have its pros and cons, it should be emphasized that any attempt to automate calculation of such a size is most desirable. There is a multitude of programs enabling its estimation is large, but in general they are limited mainly to the simulation methods. In addition, these programmes are mostly related to the broader concept of risk, where the idea of VaR plays a secondary role.

Thus, the VaR Calculator presented above is a proposal which, thanks to its obvious advantages, may serve as an alternative for commercial applications of this type. All the possibilities of a flexible approach to the determinants of VaR, which allow them to be freely modified, seem to be its essential asset. As already mentioned, the calculator allows the user to determine Value at Risk estimates for different levels of confidence and at the same time different numbers of historical observations. This allows additional analysis and examining the impact of these factors, depending on the changing values of these elements [13]. It is also significant that the programme does not impose the values of the model parameters necessary for their estimation, which is crucial for the parametric methods. Therefore, it is possible to check estimation effectiveness e.g. for changing *l* levels [14]. In addition, many different approaches to VaR proposed are a significant advantage of the programme. They include simulation and parametric methods, with various ways of handling the behaviour of financial instruments in the portfolio[5] [14]. The fact that all the estimates of value at risk are determined along returns rates, prices of the subjects analysed and direct profits and losses is also important.

As the *Value at Risk* is quite broad in terms of different varieties and, for example, approaches to modelling the random disturbances, the authors of the *VaR Calculator* can continue developing the application. Soon, an update will be proposed, with the so-called long-term predictions based on the concepts outlined so far.

Notes

[1]The Mean Reversion model is often called Ornstein-Uhlenbeck model.

[2]The jump-diffusion process consists of geometrical Brownian motion combined with the Poissonian process.

[3]http://prz.edu.pl/~jacekb/software/freeware/VaR/.

[4]http://www.statsoft.pl/Zasoby/Do-pobrania/Wersja-probna-STATISTICA.

[5]the concepts based on variability models created using the exponentially weighted moving average and the GARCH class models.

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