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Full Length Research Paper

Application of VaR in emerging markets: A case of selected Central and Eastern European Countries

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The possibility of market risk quantification in global recessive business conditions is especially significant in investment processes on emerging markets. Thus, in this paper, we investigate the relative performance of Value at Risk (VaR) methods with the daily returns series of four different emerging markets. The research covers the sample representing Slovenian (SBI20), Croatian (CROBEX), Serbian (BELEXline) and Hungarian (BUX) stock indices. The tested VaR methods are the Historical simulation (HS) and Delta normal VaR with rolling windows of 50, 100, 200 and 250 days. Subject of this research is to determine the possibility of application of the HS and Delta normal VaR with 95% and 99% confidence level in investment processes on the emerging markets of the selected Central and Eastern European countries. The applied methodology during the research includes analyses, synthesis and statistical/mathematical methods. The main goal of the research is to test the performance of the HS and Delta normal VaR with 95% and 99% confidence level estimates as functions of determining the maximum possible loss from investment activities on emerging markets. Research results indicate that methods shown to afford accurate VaR estimates in developed markets do not necessarily have application on the emerging markets.

Key words: Value at risk, emerging markets, risk management, historical simulation, Delta normal VaR, investment processes, VaR backtesting.

INTRODUCTION

Under the conditions of global financial crisis, risk management has an extremely important role in the investment processes on the financial markets. Risk, as such, can be defined as the probability of occurrence of undesired results and consequences. Namely, market risk represents the result of the change in the value of papers of value on the capital market (Bessis, 2002). One of the most intuitive and most reasonable methods of managing market risk is the Value at Risk (VaR) method. The need for quantification of market risk of the most important financial institutions was pointed at in the beginning of the 70`s of the previous century as a result of the increase of the financial instability. Baumol (1963) investigated the quantification of market risk based on the standard deviation adapted to the parameters of the level of confidence which reflects the inclination towards risk. However, this measurement of market risk does not differ from the VaR method, which is defined as "*the worst loss over a target horizon with a given level of confidence"* (Jorion, 2007). VaR is a statistical measurement of the maximal probable losses from investment activities, and those losses that surpass the value of VaR happen only under specified probability (Linsmeier and Pearson 2000) . The popularity of VaR, and consequently the de-bates among the scientific and professional public about the validity of the applied statistical suppositions comes to life especially after JP Morgan enabled the RiskMetrics system publically available through the Internet in 1994. This is because VaR is essentially a point estimate of the tails of the empirical distribution. VaR completely ignores statistical properties of losses beyond the specified quantile of the profit-loss distribution, i.e. the tail risk. In order to overcome these drawbacks, Artzner et al. (1997)

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proposed the Expected Shortfall (ES) as an alternative risk measure. It is defined as the conditional expectation of loss beyond a fixed level of VaR. As such, ES takes into account tail risk and satisfies the sub-aditivity property, which assures its coherence as a risk measure. The limitation of ES is that it employs historical data from recent past, thereby allowing for the presence of heavy tails without making assumptions about the probability distribution or dynamics of returns. Beyond the traditional approaches, there is an alternative which uses the Extreme Value Theory (EVT) to characterize the tail behavior of the distribution of returns. By focusing on extreme losses, the EVT successfully avoids tying the analysis down to a single parametric family fitted to the whole distribution. McNeil and Frey (2000) and Embrechts et al. (2008) survey the mathematical foundations of EVT and discuss its applications to financial risk management. The EVT approach is also a convenient framework for the separate treatment of the tails of a distribution which allows for asymmetry. Considering that most financial return series are asymmetric, the EVT approach is advantageous over models which assume symmetric distributions such as *t*-distributions, normal distributions, ARCH, GARCH-like distributions except E-GARCH which allows for asymmetry. There are several constraints of EVT. Namely, sample size, i.e. we need to observe some events which constitutes extremes and most estimation methods for the threshold optimazation depend on subsample bootstrap, which implies that previously mentioned constraint has to be observed in all bootstrap subsamples. Next, it suffers from the same curse of dimensionality problems as many other techniques, such as GARCH. Further, EVT assumes the data are IID (independent and identically distributed).

A special challenge is the possibility to apply VaR on the financial markets in emerging countries, i.e. emerging markets. Namely, in the literature at subject there is a fundamental difference between the developed and the emerging markets according to their different characteristics. The world`s most developed market economies are generally considered to be more liquid and efficient then the economies of the developing countries. The application of the VaR methods on emerging markets requires special attention, especially regarding insufficient liquidity, small scale of trading and historically speaking, asymmetrical and low number of trading days with certain securities. The financial theory points to the fact that higher volatility which is characteristically for the returns of the emerging markets corresponds to the higher expectations of returns on those markets (Salomons and Grootveld 2003) . Emerging markets grew exponentially in terms of trading volume, number of listed companies, and market capitalization (Goetzmann et al., 1999). Bekaert and Harvey (1997) point to that a high number of emerging markets become more and more integrated into the global financial market. However, the distinction of these markets in relations with the developed markets is seen through high liquidity risk and the restricted number of shares with high market capitalization. Also, compared with the developed markets, emerging markets are characterized by reforms of the financial market, frequent internal and external financial shocks, high level of country risk (i.e. political risk, economic risk and financial risk), changes of the credit rating, fluctuation of the foreign currency courses, high level of insider trading, etc. The factors named above influence the growth of the volatility of the emerging markets and consequently on the growth of the deviation from the normal distribution, which results in the impossibility to adequate predictions of the market risk in investment processes. Also, the methods of quantification of market risk which as a base have the supposition of normal distribution are less reliable in emerging markets.

The application of the VaR methodology, which is basically created and developed for liquid markets, expects a special testing in emerging countries, which are characterized by extremely volatile and `shallow` financial markets. The implementation of the VaR methodology in investment processes directly corresponds to the choice of the adequate methodology. The most important characteristic of the chosen method is to precisely determine the probability of the losses. Number of violations of estimates provided at various confidence levels should be consistent with those levels. Applicable methods provide better VaR estimates at higher confidence levels, while other methods consider instationary nature of volatility (Mahoney, 1996). The most of these studies in the examined field point to the adequacy of application of the VaR on the financial markets of the developed countries, while the applicability of this method has not been tested broader in the emerging markets, yet.

This paper tests the possibility of application of the VaR methods on emerging markets of selected Central and Eastern European countries. Therefore, the research goal is to determine whether commonly used VaR methods adequately capture market risk on the emerging markets of Slovenia, Croatia, Serbia and Hungary. Although different in some aspects, these countries have a common denominator being either EU member states or countries in EU integration process. Also, they have emerging economies and are seen as an interesting investment opportunity for investors looking to diversify their portfolio. In this paper we examine the theoretical background and performance of two methods for VAR calculation in emerging markets - historical simulation (HS) and Delta normal VaR. The paper evaluates and analyses the out of the sample forecasting accuracy of both methods on Slovenian (SBI20), Croatian (CROBEX), Serbian (BELEXline) and Hungarian (BUX) stock indices. It is the central objective of this paper to test the possibility of application of the VaR calculation methods on return series generated by the given stock indexes. Thus, the main motivation for this research is to provide up to date evidence on the risk management and return characteristics of emerging markets over time. Results of this research will be especially interesting to both domestic and foreign investors in global recessive business conditions. Further, obtained results are significant both at the microeconomic (company) and macroeconomic (economic, political, social, etc.) level. We present empirical evidence of the possibility of VaR methods application in the emerging markets of the selected Central and Eastern European countries.

Theoretical background

Linsmeier and Pearson (2000) have defined VaR as the worst expected loss over a given horizon under normal market conditions at a given confidence level. VaR represents a method of quantification of the market risk with the usage of standard statistical techniques. The calculation of VaR in investment processes understands an adequate perception of confidence level, the time horizon and value. Namely, the time horizon points to the size of the potential loss, as well as to the prediction of the market risk, while confidence level determines the reliability of the market risk quantification in investment processes. The chosen confidence level of the VaR determines how many VaR breaks, i.e. where the return of an investment exceeds the estimated VaR measure, should occur. The viewed time horizon and confidence level influence on the validity of the predictions of the maximal possible loss from investment activities. Great financial crisis in the past have influenced on the development of the model of managing market risk. Risk management gained importance in the last decade due to the increase in the volatility of financial markets and a desire of a less fragile financial system (Gencay et al., 2003). The approval of the Basel Committee for the implementation of internally developed VaR models as functions of quantifications of market risk has influenced the development of various methods of VaR calculations (Fernandez, 2003). The Basel Accord was concluded in 1988 and fully implemented in the G-10 countries (Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, the United Kingdom and USA) in 1992 (Saunders, 1999).

The estimation of the market risk is best to quantify by VaR (Jorion, 2002). The advantage of the VaR is that it can be applied to almost any subject of investment and that it is theoretically simple. However, the disadvantage of the VaR is that there exist a great number of possible calculations, each of the methods with its own advantages and disadvantages. An extreme importance for the adequate predictions of market risk has the volatility, which is subdued to change through time (Hopper, 1996). Therefore, that implies the approval of the application of different VaR methods. Degiannakis (2004) points out that different technique of volatility are applied with different goals and objectives, and that the modeling of volatility is necessary for estimating the VaR. It has been empirically proven that the volatility of returns is not constant from day to day, but varies over time. Linsmeier and Pearson (1996) conclude that there is no simple answer to the question which VaR method is better during the quantification of the market risk and implementation. Different characteristics of returns on the subject of investment, i.e. the statistical characteristics of returns such as volatility, kurtosis and skewness can influence the calculation and the choice of the VaR methods. Mostly of VaR methods are based on the normality of distributions, but many empirical studies have shown that the distribution of returns is not normal (Duffie et al., 1997), and so accordingly VaR overestimates or underestimates the real market risk in a certain number of cases.

The advantages of the application of VaR during the quantification of market risk in investment processes are numerous. Namely, VaR enables a simple and consistent measurement of market risk for various positions and factors of risk. Also, it takes into consideration the coefficients of the correlations between various factors of risk, which results in the low level of the total investment risk (Dowd, 2002). VaR measures have their weaknesses. A good risk measure needs to be more than just appropriately conservative and accurate (Huang and Lin, 2004). The standard error of a VaR measure increases as confidence level increases. At a 99% confidence level, different VaR methods, such as the Delta normal VaR, produce larger VaR measure deviations than they do at a 95% confidence level (Su and Knowles, 2006). Beder (1995) and Angelidis et al., (2004) conclude that the results of the applications of the VaR are too imprecise, having in mind that different VaR measures give extremely different estimates of market risk using the same data. Galindo Martin et al. (2007) argue that risky investments are accepted when there is a high confidence that there will be high future returns. Bearing in mind the above mentioned facts, it is necessary to adequately classify the market risk in investment processes, as well as to execute their predictions.

The most common methods for VaR estimation are the historical simulation (HS VaR), parametric VaR (Delta normal VaR) and Monte Carlo simulation. Generally viewed, none of these VaR calculations perform superior to others in all circumstances and markets (Hendricks, 1996). Even though all of these three methods of the VaR calculation differ from each other, they have certain common characteristics. Each of the methods uses risk factors, as well as a historical distribution of price variations on the market. Also, a common problem is the choice of the time horizon from which the historical data are taken from as a base for the prediction of future distribution of the turnover of the subject of investment (Kritzman and Don, 2002).

In our work the possibility of the historical and parametric methods of VaR calculations are explored in emerging markets of the selected Central and Eastern European countries. Since the historical VaR is a non-parametrical method, returns are not distributed according to a specific probability distribution. HS VaR is characterized by the simplicity of the calculation of the VaR and gives a relatively reliable result (Dowd, 2001). The calculation of the HS VaR understands the supposition of the usage of the historical distribution of the changes in prices. This supposition is the source of the significant objections to this method. Also, the HS VaR demands an enormous size of data to perform well at higher confidence levels (Jorion, 2006). When tested in developed markets (e.g. USA and Europe), historical simulation has been shown to offer reasonable VaR estimates for at least 95% confidence level. However, emerging markets have their own volatility peculiarities that need to be taken into account. The parametric method (Delta normal VaR) of measurement is conducted in a way to suppose that the distribution of returns corresponds to one of the theoretical distributions, such as is e.g. normal distribution. According to this supposition, the VaR calculation is conducted on the basis of the middle value of the gains/losses (or the rate of the turnover) and standard deviation of the examined data. Even though for the parametric method of calculating VaR it is not necessary to suppose that the gains/losses (or the rate of the turnover) are normally distributed, normal distribution is most often used (Jorion, 1996).

Gencay and Selcuk (2004) examined the relative performance of VaR models with daily stock market returns of nine different emerging markets. In this paper we examined the possibility of historical and Delta normal VaR methods with 95 and 99% confidence level application on the stock indexes in the emerging markets of the selected Central and Eastern European countries. These VaR methods are commonly used to predict the market risk in investment processes on the largest global financial markets. Similarly, Zikovic and Aktan (2009) investigated the relative performance of a wide array of VaR models with daily returns of Turkish and Croatian stock index. They concluded that only advanced and theoretically sound VaR models such as EVT and HHS, can adequately measure equity risk on Turkish and Croatian equity markets in times of crisis. Contribution of this paper is the empirical investigation and analyses of the applied HS and Delta normal VaR methods on the daily stock index returns of four different emerging markets.

MATERIALS AND METHODS

In this article two approaches have been used to quantify the market risk in investment processes, that is for determining the maximum possible loss from investment activities. One of the approaches is non-parametric and the other is parametric. As the representative of the non- parametric approach, the historical simulation VaR method has been used, while for the parametric approach, the Delta normal VaR method has been applied. The goal of the research in this paper is to determine the level of success of the application of the HS and the Delta normal VaR method with 95% and 99% confidence level as functions of predicting the market risk in investment processes, i.e. the maximum possible loss from investment activities on emerging markets. The sample of the research comprises daily returns of stock indexes of selected Central and Eastern European countries, i.e. Slovenia, Croatia, Serbia and Hungary. The tested stock indexes are SBI20, CROBEX, BELEXline and BUX, in respect, during the period between 10.01.2006 – 01.04.2009. The research has been conducted during this period, due to the accessibility of historical data for the stock indexes of the named emerging markets. The applied methodology during the research includes analyses, synthesis and statistical/mathematical methods. The mathematical part of the research has been realized through Microsoft Excel software.

On the basis of the calculated values of the HS and the Delta normal VaR with rolling windows of 50, 100, 200 and 250 days, their success have been monitored in predicting the market risk in investment processes for the next day. The prediction of the market risk on the basis of the VaR was successful in case the value of the accumulated loss from investment activities was less than the value of the VaR of the previous period. Analogically, the prediction of the market risk was not successful, in case the value of the accumulated loss from investment activities was more than the value of the VaR of the previous period. The procedures have been carried out for the HS and the Delta normal VaR with 95 and 99% confidence level. Having in mind the basic characteristics of the VaR calculation methods, it could be expected that 95% confidence level is appropriate for application in stable market conditions, while 99% confidence level is appropriate for application in volatile market conditions. At the beginning of the analysis, the distribution of the sample has been tested with the Kolmogorov-Smirnov test, with an objective to determine whether the sample has normal distribution. On the basis of the central dispersive parameters, the picture of the distribution of the sample was gained. The normal distribution of sample means that the coincidental variable (x), with the arithmetical middle μ and the standard deviation , is normally distributed in case the function of probability f(x) gives the variable (x) the value of X, following the next function of probability:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right] \quad (1)$$

Where: - standard deviation, – pi, constant = 3,14159…, and – arithmetical middle.

Also, during the testing of the sample, its characteristics have been examined - skewness and kurtosis. Their coefficients have been calculated according to the next formulae:

$$\text{Coefficient skewness} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \overline{x}_n\right)^3}{\left(\overline{s}_n\right)^3} \quad (2)$$

$$\text{Coefficient kurtosis} = \frac{\frac{1}{n}\sum_{k=1}^{n}\left(x_i - \overline{x}_n\right)^4}{\left(\overline{s}_n\right)^4} \quad (3)$$

where: X_i - sample, $\overline{X}_n$ - middle of the sample and $\overline{S}_n$ - dispersion of the sample.

Kolmogorov–Smirnov test is used to test whether two underlying one dimensional probability distributions differ. The random process F(x) is formed as the estimation problem and used as the test statistic the RV:

$$q = \max_x |\hat{F}(x) - F_0(x)| \quad (4)$$

This choice is based on the following observations: For a specific ,

the function $\hat{F}$ (x) is the empirical estimate of (x) it tends, therefore, to F(x) as n . From this it follows that:

$$E(\hat{F}(x)) = F(x), \hat{F}(x) \quad F(x), (n) \quad (5)$$

This shows that for large n, q is close to 0 if H_0 is true and it is close to F(x) – F_0(x) if H_1, is true. It leads, therefore, to the conclusion that we must reject H_0 if q is larger than some constant c. This constant is determined in terms of the significance level = F {q > c|H_0} and the distribution of q. Under hypothesis H_0, the test statistic q. Using the Kolmogorov approximation, we obtain:

$$\alpha = P\{q > c | H_0\} = 1 - e^{-2nc_2} \quad (6)$$

The test thus proceeds as follows: Form the empirical estimate $\hat{F}$ (x) of F(x);

$$\text{Accept } H_0 \text{ if } q > \sqrt{\frac{1}{2n} \ln \frac{\alpha}{2}} \quad (7)$$

The resulting Type II error probability is reasonably small only if ***n*** is large. As stated in the previous section of this article, the used methods of the VaR calculations have certain advantages and disadvantages. Accordingly, in the examination both of the methods were used on the stock indexes of emerging markets, in order to establish which of the two methods is more adequate to monitor the level of the maximum loss from investment activities. In the examination the number of the days of successful predictions were analyzed in parallel with the number of unsuccessfully predicted market risk in investment processes of the HS and the Delta normal VaR with 95 and 99% confidence level with rolling windows of 50, 100, 200 and 250 days. For each of the stock indexes, the success of the predictions of market risk were analyzed on a daily basis; more over with the dependence upon the length of the interval (number of days) for what the calculation of the VaR was carried out. The analyzed period of the examination has been divided into four segments. The first segment represents the period upon which the VaR values were calculated, and it represents the basis for its calculations (the year 2006), while in the second, third and fourth segment the success of the application of the HS and the Delta normal VaR were tested with rolling windows of 50, 100, 200 and 250 days. The second segment represents the data of returns (daily return series) of the stock indexes for 2007, the third for 2008, and the fourth for 2009. The limitation in the research was the non existence of a longer time period that could have been analyzed, because these tested emerging markets are in the early phase of development, whose important growth is expected in the forthcoming period. The returns on the stock indexes tested in this paper are calculated as:

$$r_t = \ln(1 + R_t) = \ln \frac{P_t}{P_{t-1}} \quad (8)$$

where, R_t – return on stock index during a period t, P_t – stock index price during a period t and P_{t-1} – stock index price during a period t-1.

In order to understand the various methods of VaR calculation, it is necessary to examine a mathematical definition of VaR. If X is defined to be the loss on a portfolio, and p the confidence level, then VaR is defined by:

$$P(X \leq VaR) = \pi \quad (9)$$

This is equivalent to:

$$F_x(VaR) = \pi \quad (10)$$

Where, $F_x = P(X \leq x)$ is the probability distribution function of the random variable X. Thus, it is clear that if the probability distribution function of X is known, then VaR is given by:

$$F_x^{-1}(\pi) = VaR \quad (11)$$

Where, $F_x^{-1}(\bullet)$ denotes the inverse of $F_x(\bullet)$. This mathematical definition of VaR demonstrates that VaR is a function of p, the confidence level, and N, the time horizon.

The method of historical simulation is the simplest method of obtaining a profit and loss distribution of a portfolio. The method estimates the quantiles of an underlying distribution from the realization of the distribution and it requires a database of returns for the stocks comprising portfolio. The returns can be used to obtain an empirical distribution function for the losses on the portfolio by converting the return losses into an ordered set $X_1 \leq ... \leq X_N$. The empirical probability distribution for the losses on the portfolio is defined by:

$$P(X \leq x) = \begin{cases} 0, x < X \\ i/N, X_i \leq x \leq X_{i+1} \\ 1, X_N \leq x \end{cases} \quad (12)$$

Thus, for a confidence level of p=0.95, and a data set of 100 observations, VaR would be given as the 95th loss in ordered set. The smallest probability that can be obtained such that $P(X \leq VaR)$ is 1/N. HS VaR method accurately reflects the historical probability distribution of the market variables.

The Delta normal VaR is the method among the various ones used to estimate the VaR. Let the sample of observations be denoted by r_t, t=1,2,...,n where n is the sample size. Let us assume that r_t follows a martingale process with $r_t = \mu_t + \varepsilon_t$ where $_t$ has a distribution function F with zero mean and variance, $_t^2$. The VaR in this case can be calculated as:

$$VaR_t(\alpha) = \mu_t + F^{-1}(\alpha)\sigma_t \quad (13)$$

Where $F^{-1}( )$ is the q^{th} quantile (q=1-) value of the unknown distribution function F.

An estimate of $_t$ and $_t{}^2$ can be obtained from the sample mean and the sample variance by:

$$\hat{\mu}_t = \frac{1}{n}\sum_{i=1}^{n} r_i, \quad \hat{\sigma}_t^2 = \frac{1}{n-1}\sum_{i=1}^{n}(r_i - \hat{\mu}_t)^2 \qquad (14)$$

Although sample variance as an estimator of the standard deviation in Delta normal VaR is simple, it has drawbacks at high quantiles of a fat-tailed empirical distribution. The quantile estimates of the variance–covariance method for the right tail (left tail) are biased downwards (upwards) for high quantiles of a fat-tailed empirical distribution (Gencay and Selcuk 2004).

As for the out of sample VaR backtest, the Kupiec test was used with 95% and 99% confidence level, and on the basis of it we have accepted or rejected the success of the application of the named method of VaR calculation. Jorion (2001) state that the number of VaR breaks is expected to be the same as one minus the level of confidence. So, for a sample of 100 observations where 95% confidence level VaR is calculated, we would expect five (100% - 95% x 100 = 5) VaR breaks to occur. In the paper this is called the target number of VaR breaks. If there are more or less VaR breaks than expected, it is because of deficiencies in the VaR method or the use of an inappropriate VaR method. A widely used backtest is the Kupiec test. This test uses the binominal distribution to calculate the probability that a certain number of VaR breaks will occur given a certain confidence level and sample size. The Kupiec Test function is (Veiga et al., 2008):

$$P(x|n,p) = \binom{n}{x} p^{x}(1-p)^{n-x} \qquad (15)$$

The variable x is the number of VaR breaks, N the sample size and p corresponds to the level of confidence chosen for the VaR method (making a 95% confidence level a 5% probability input for the method). If the sample size is inputted and p is set to one minus the level of confidence, the binomial function produces the likelihood that a specific number of VaR breaks is to occur. By using the cumulative binomial distribution, it is possible to calculate an interval within which the number of VaR breaks must fall, in order for the method to be accepted. This is done by calculating for which values of N that the cumulative binomial distribution produces probabilities that are in the interval 2.5%<P<97.5% (which corresponds to a 95% test confidence). VaR methods that produce values of N that lies within this range can therefore be accepted. If the method produces values of N outside this span, the method is rejected. A rejection means that the confidence level that we used in the VaR method did not match the actual probability of a VaR break. This in turn indicates that the method is not performing well and that it should be rejected.

Data and preliminary analysis

Due to data availability and possibility of its dynamic processing and monitoring, i.e. application performance of the Historical Simulation (HS) and Delta normal VaR methods, sample in the research comprises stock indexes from selected Central and Eastern European countries for the period 10/01/2006 – 01/04/2009 (831 days). For emerging countries, a significant problem for a serious and statistically significant analysis is the short histories of their market economies and active trading in financial markets. It is practical to analyze the stock indices of these countries, because of the short time series of returns of individual stocks. The stock indices can be viewed as a portfolio of selected stocks from an individual emerging market. Thus, data used in the analyses of HS and Delta normal VaR methods are the daily return series from Slovenian (SBI20), Croatian (CROBEX), Serbian (BELEXline) and Hungarian (BUX) stock indexes. The data are collected from each official stock exchange web site. The tested VaR methods are HS and Delta normal VaR with rolling windows of 50, 100, 200 and 250 days. VaR methods are calculated for a one-day ahead horizon with 95 and 99% confidence level, i.e. coverage of the market risk. To secure the same out of the sample VaR backtesting period for all of the tested stock indexes, the out of the sample data sets are formed by taking out 579 of the latest observations from each stock index. The rest of the observations are used as presample observations needed for HS and Delta normal VaR starting values. The out of the sample VaR backtesting period includes the latest financial market crisis in the global and regional financial markets. Out of the sample VaR backtesting period has been divided into three parts, and following years (2007, 2008, and 2009).

In 2009, the examined period consists of the first quarter of the year. For each of the examined stock index the values of the HS and the Delta normal VaR have been calculated with rolling windows of 50, 100, 200 and 250 days. On the basis of the received values of the VaR methods for the above mentioned rolling windows the performances of their application are tested as functions of the market risk prediction in investment processes. In case the predicting of market risk on the basis of VaR value was adequately calculated for the next day, the method was considered successful. However, the application of the VaR method was considered unsuccessful in case the predicting of the market risk was inappropriate, that is, a higher loss was perceived then predicted. This way a sequence of days was formed of successful and unsuccessful predictions of the market risk of the HS and Delta normal VaR. The procedures were applied on 95 and 99% confidence level. The validity of the analysis (VaR backtesting) was tested by the Kupiec test with 95 and 99% confidence level. At the beginning of the research, the test of normal distribution was conducted, where it was tested whether the analyzed returns of stock indexes (the data) have a normal distribution. On the basis of the Kolmogorov-Smirnov test, it can be said with great certainty that stock index returns are not normally distributed, that is, there are important differences among the distribution in the samples and the normal distribution. Table 1 shows the results of the normal distribution. Parameters of standard deviation, variance, skewness and kurtosis point to the basic characteristics of the sample (Table 2). According to skewness, the curve of the stock index of SBI20 has an asymmetrical appearance, and the curve of distribution binds towards higher values (to the right side) . The results for CROBEX and BUX are identical, while the results of BELEXline are such to have an asymmetrical curve, binding towards lower values (left side). On the basis of standard deviation we can conclude that the returns are more homogenous with SBI20 and BELEXline, while the homogenousity is less with CROBEX and BUX. The values of maximum and minimum represent how significant are the deviations of minimal and maximal returns. Graphical representation of daily return changes for all stock indexes in the analyzed period is given in Figures 1 to 4. Returns from all stock indexes are stationary but far from being normally distributed. High volatility for all stock indexes is noticeable during 2008, which could be interpreted as effects of the global economic crisis on the emerging markets.

RESULTS AND DISCUSSION

This section of the paper presents and analyzes the results based on HS and Delta normal VaR estimates for

Table 1. Kolmogorov – Smirnov tests of normality for the stock indices in the period 10/01/2006 – 01/04/2009.

Stock index	Statistic	Sig.
SBI20	0.118	0.000
CROBEX	0.130	0.000
BELEX	0.130	0.000
BUX	0.077	0.000

Source: Author's calculations.

Table 2. Summary descriptive statistics for the stock indices in the period 10/01/2006 – 01/04/2009.

	SBI20	CROBEX	BELEXline	BUX
Std. Deviation	1.4010	1.7397	1.1729	1.9738
Variance	1.9629	3.0266	1.3758	3.8960
Skewness	-.704	-.179	.326	-.201
Kurtosis	7.396	11.463	13.574	7.879
Minimum	-8.30	-10.76	-6.97	-12.65
Maximum	7.68	14.78	9.87	13.18

Source: Author's calculations.

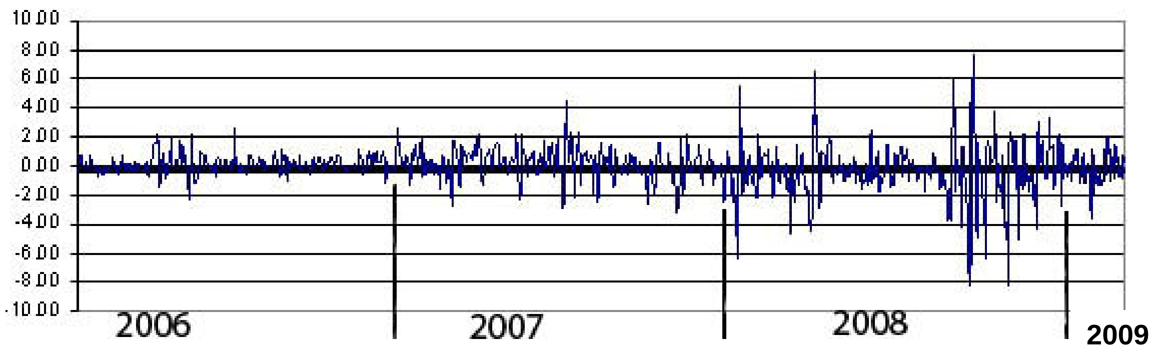

Figure 1. SBI20 stock index returns in the period 10/01/2006 – 01/04/2009. Source: Author's calculations

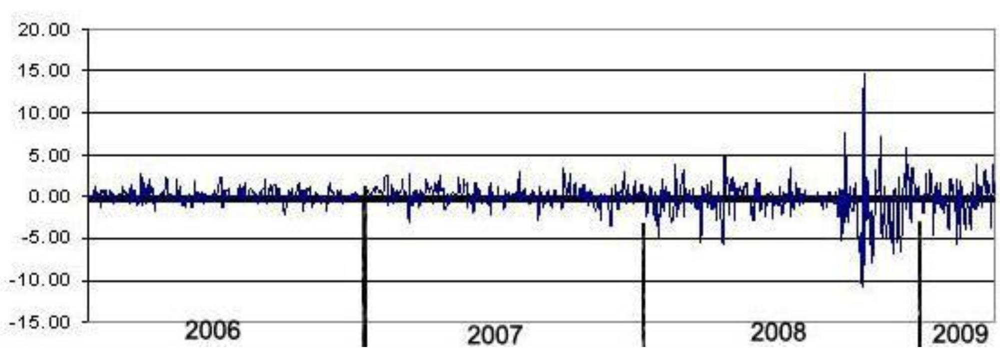

Figure 2. CROBEX stock index returns in the period 10/01/2006 – 01/04/2009. Source: Author's calculations.

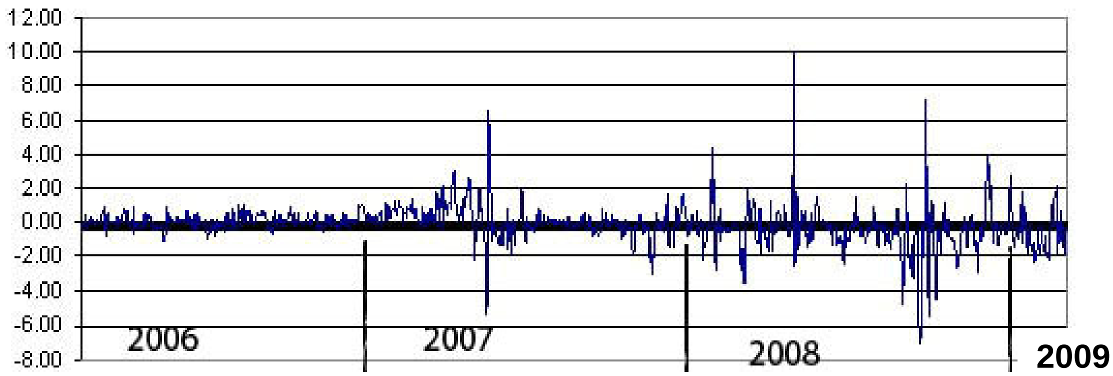

Figure 3. BELEXline stock index returns in the period 10/01/2006 – 01/04/2009. Source: Author's calculations.

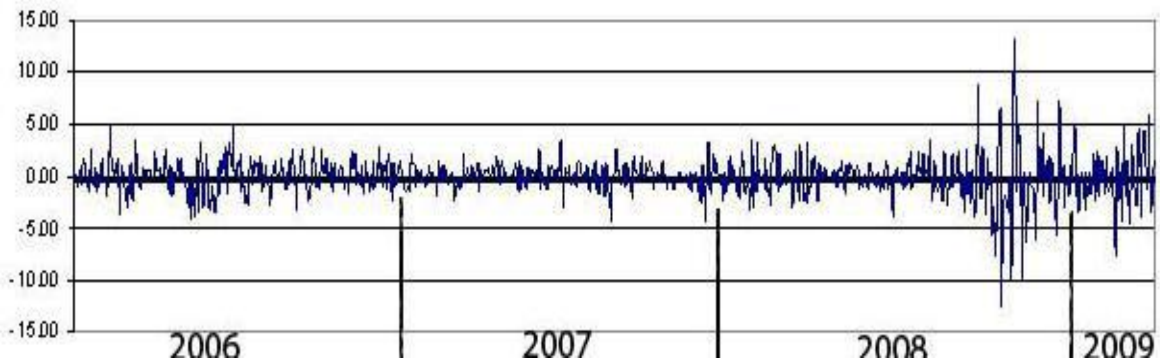

Figure 4. BUX stock index returns in the period 10.01.2006 – 01.04.2009. Source: Author's calculations.

the SBI20, CROBEX, BELEXline and BUX stock indices. HS and Delta normal VaR methods were tested as functions of determining their statistical characteristics and their possibility to predict adequately the market risk in investment processes on the emerging markets. The results of the application of HS and Delta normal VaR for the examined periods are presented in the tables (appendices), and which were tested with the Kupiec test. For each stock index the success of the application of the HS and Delta normal VaR with 95 and 99% confidence level has been tested in accordance with the number of the examined days. Out of the sample backtesting points to the success and acceptance of the method, or to their unsuccessful character and rejection. The method that is more successful is the one that shows less deviation from the Kupiec test, according to the number of days. For 2007 backtesting results show that with HS and Delta normal VaR with 95% confidence level the success of the market risk prediction in investment processes is higher for larger number of observations (days), which is concluded due to the success of the tested models (Tables A1 and A2). HS VaR with 95% confidence level has proven to be successful only with one stock index, which is BUX with rolling windows of 200 and 250 days (Table A1), while Delta normal VaR with 95% confidence level was successful with more tested stock indexes (Table A2). Namely, Delta normal VaR with 95% confidence level was unsuccessful in two cases with rolling windows of 50 (CROBEX and BELEXline) and 100 days (BELEXline and BUX), while with rolling windows of 200 and 250 days it was unsuccessful in one case (SBI20). In 2007, on the basis of backtesting results it can be concluded that with the application of the HS and Delta normal VaR with 95% confidence level a more successful prediction of the market risk was gained in investment processes for longer time intervals for which the VaR calculations were done (200 and 250 days). With 99% confidence level HS VaR was unsuccessful with rolling window of 50 days for three stock indexes (SBI20, CROBEX and BELEXline), with rolling window of 100 days for all tested stock indexes, with rolling window of 200 days for three stock indexes (SBI20, CROBEX and BELEXline) and with rolling window of 250 days for three stock indexes (SBI20, CROBEX and BELEXline), while for the same period the unsuccessful character of Delta normal VaR was shown for three stock indexes (SBI20, CROBEX and BELEXline), for two stock indexes (SBI20 and BELEXline), for one stock index (SBI20) and for one stock index (SBI20) in correlation to the number of days, respectively (Table A7 and A8). According to this, the backtesting results show that the success of application the Delta normal VaR with 95 and 99% confidence level for 2007 were higher than that of the results shown by HS VaR with the same confidence level.

In 2008, both of the methods with 95% confidence level have proven to be unsuccessful for all tested stock indexes, with the fact that there are less visible deviations noticed for shorter periods, while the number of VaR breaks increased according to the increase of the length of the observed period (Tables A3 and A4). It can be concluded that none of the observed methods performs superior to other for 95% confidence level, because there are no regularities which would be confirmed in all cases. The success of the HS and Delta normal VaR with 99% confidence level is almost alike, namely, that with both of the methods for all of the intervals for which the calculations were conducted, the results show failure for all tested indexes. However, if the number of days that deviate from the Kupiec test is being analyzed, it becomes visible that the HS VaR, even though unsuccessful, had fewer deviations as compared with the Delta normal VaR (Tables A9 and A10). Analyzing the backtesting results for 2008, the HS and the Delta normal VaR with 95 and 99% confidence level, both of the methods have proven to be unsuccessful for all tested stock indexes with rolling windows of 50, 100, 200 and 250 days. The only difference is seen in the number of unsuccessful days of predicting the market risk in investment processes, but even in that part are mainly similar results with both of the methods. In 2008, the downfall of stock indexes under the expected and intense emerging markets volatility have evidently influenced on the success rate of the predictions of market risk in investment processes, which are confirmed with the backtest results.

In 2009, HS VaR with 95% confidence level was unsuccessful once, and that with rolling window of 50 days with BELEXline, while with other stock indexes there are no unsuccessful predictions (Tables A5 and A6). Delta normal VaR with 95% confidence level was successful in all cases. According to the backtesting results, it can be concluded that the level of success of both of the methods was higher for the larger number of days. Also, the success rate was the same for both of the methods with 99% confidence level and in all cases (Tables A11 and A12). With both of the methods with 99% confidence level the success rate was higher for the larger number of days, i.e. the larger number of days causes smaller number of unsuccessful market risk prediction in investment processes. In 2009, a sharp fall of trading on the emerging markets has occurred, which can also be seen by the conducted analysis. In this period, there is the biggest success of the prediction of market risk in investment processes, which is the result of the small scale of trading, less amount of cash flow in trading, low level of liquidity, low market capitalization, small volatility, etc. Therefore, the value of stock index returns is not subdued to significant changes, and with that the determination of the maximal possible loss from investment activities was also more successful. Having in mind the results of the mentioned backtest in 2007, the success of the application of the Delta normal VaR with 95 and 99% confidence level is bigger than of HS VaR with the same confidence level. With 95% confidence level, none of the tested methods performs superior to other for all the observed intervals in 2008. Namely, due to the scattered characteristics of the results we cannot determine for which interval (number of days) is the application of the HS or the Delta normal VaR method more successful. The tested methods of VaR have proven to be unsuccessful for all tested stock indexes. Thus, performance of one method is not superior than other, especially if the prediction of the market risk is analyzed according to number of days which deviate from the Kupiec test. If we analyze the success of application of the HS and the Delta normal VaR with 99% confidence level for 2008, both of the methods were unsuccessful for all tested stock indexes. However, if we analyze the number of days which deviate from the Kupiec test, the deviations are less with HS then with the Delta normal VaR, and a slight advantage can be given to HS VaR under the given circumstances.

For 2009, we cannot determine the interval in which the HS or the Delta normal VaR would be more successful, both for 95 and 99% confidence level, and not under any condition, because the results are scattered, i.e. there is no rule that could be determined. Having all mentioned above in mind, findings of tested stock indexes in the period 2007 - 2009 imply the basic figures for the period 2010 - 2012. Namely, due to volatility and characteristics of selected emerging markets it is practical to observe findings in 2007 (first period), 2008 (second period) and 2009 (third period). First period is characterized by stability and positive conjuncture, second period is characterized by expressive volatility and third period by moderate volatility. Forecasting for the period 2010 - 2012 is based on the backtesting results in the observed periods (2007, 2008 and 2009). Basic assumption is that the market characteristics and conditions on the selected emerging markets in the period 2010- 2012 are expected to be similar as those in the observed periods. According to the backtesting results in 2007 for 95 and 99%

confidence level, it can be estimated that the success of application the Delta normal VaR is going to be higher than that of the HS VaR in the period 2010 - 2012. Namely, the estimated number of days for both methods which deviate from the Kupiec test is in the interval from -11 to 5 for 95% confidence level and from -9 to 1 for 99% confidence level for all tested stock indexes in the period 2010 - 2012. Backtesting results in 2008 imply that none of the tested methods performs superior to other and that the estimated number of days which deviate from the Kupiec test is in the interval from -25 to -2 for 95% confidence level and from -16 to -5 for 99% confidence level for all tested stock indexes in the period 2010 - 2012. Similar effects can be expected having in mind the backtesting results in 2009, while the estimated number of days which deviate from the Kupiec test is in the interval from -5 to 4 for 95% confidence level and from 0 to 1 for 99% confidence level for all tested stock indexes in the period 2010 - 2012.

Conclusion

The findings of this research show beyond any doubt the necessity of applying market risk estimation methods, i.e. HS and Delta normal VaR in the framework of a broader analysis of investment processes in emerging markets. The results in this research indicate that methods shown to afford accurate VaR estimates in developed markets do not necessarily have global application. It is clear that emerging markets such as those of selected Central and Eastern European countries have unique characteristics, i.e. volatility peculiarities that need to be considered when implementing a VaR calculation procedure. Backtesting results suggest that for 95% confidence level the Delta normal VaR has proven to be more successful, while for 99% confidence level, the HS VaR had a slight advantage over the Delta normal VaR in the observed period. It undoubtedly proves the significance of the application of both of the methods of calculating VaR during the calculation of predicting the market risk in investment processes, i.e. the maximal possible loss from investment activities. It depends on the type and the characteristics of the analyzed sample of the research, which method will be more successful for prediction, especially if having in mind the fact that we cannot influence the distribution of returns, which greatly influences the choice of the method of VaR calculations. It is the level of market capitalization, level of liquidity, the number of the participants and other factors that influence the value of the stock indexes. Due to the backtesting results, it is concluded that the higher the volatility and the turnover of the trade are, the harder it is to predict the market risk. Analogically, the success of the prediction is positively influenced by smaller level of volatility and market participants, which is concretely proven by the results of proven by the results of the research. According to the obtained results, it is confirmed that the application of the tested VaR calculation methods is adequate with 95% confidence level in stable market conditions. Next, the application of the tested VaR calculation methods is adequate with 99% confidence level in volatile market conditions. Hence, it is confirmed that there is a cause-effect relation link between 95 and 99% confidence level and the stability/volatility of the selected emerging markets.

At the microeconomic level (company) the results of the research are significant, especially regarding capital allocation. Namely, if the chosen method of VaR calculation consistently overestimates the return, it causes an excessive capital allocation (more than necessary) and consequently a loss of interest rate income. On the other hand, a consistent underestimation of the risk results in less required capital allocation. In practice, one hardly knows whether an applied method will underpredict or overpredict the risk in the investment processes. At the macroeconomic level, the results of the research are significant for public policy makers. They point out to the possible future behaviour of economic systems of selected emerging countries in terms of stability and volatility. In that way, an adequate economic policy can be created and implemented with special attention on further growth and development of the selected emerging markets. Having in mind that emerging markets which are characterized by considerable oscillations in the values of stock indexes and the complexity of determining the regularities for longer periods have been analyzed, it is advisable to use both of the methods and to continuously monitor the results of performance of both the HS and Delta normal VaR.

This research also has its share of limitations. Thus, insufficient liquidity of the emerging markets of selected Central and Eastern European countries, small scale of trading and historically speaking, asymmetrical and low number of trading days, limited historical trading data and intense market volatility, the choice of the time horizon, the risk in the borders of distribution, low turnover with small number of transactions during the trading day, and frequently, no transactions at all for several consecutive days are limiting factors in this research. These factors present a significant limitation which directly effects the calculation and application of the HS and Delta normal VaR methods, that is, the successful predictions of market risk in investment processes. On the developed markets these methods enable better results, because the markets are more arranged and stabile, which result in a low level of volatility on the daily basis, and thus the predictions are more successful.

Even though the value of returns of the tested stock indexes did not have a normal distribution, the application of the Delta normal VaR was more adequate in certain cases than the HS VaR. According to this fact, and to the results of the backtesting, we find that it would be desirable to use a wide specter of different VaR methods in emerging markets, especially in the times of global recession, to predict the possible market risk in investments processes. This way the possibility of VaR breaks is narrowed, even though an outcome like that is more possible because emerging markets are not developed enough to prevent the occurrence of extremes. Slight deviations from the projected value represent loss, but the question is which amount of loss could be taken without considerable consequences, and which amount of loss brings unreturneable damage. Tail estimates can influence on the decrease of market risk in investment processes by projections of the maximal possible loss from investment activities. After some time and liquidity growth on the observed emerging markets, it will be possible to adequately analyze of both HS and Delta normal VaR methods performances, that is, which method have more efficient results in predicting the market risk in investments processes. Dependence on only the past realized data can give seriously distorted estimates of true level of market risk. Beside HS VaR and Delta normal VaR, other methods of calculating VaR in emerging markets have yet to be tested in accordance with volatile peculiarities of each tested emerging market. In investment processes on emerging markets, it is necessary to test the magnitude of deviations of the gained losses from the predicted values of the maximal possible losses from investment activities. According to backtesting performance, the courses of further researches imply continuous monitoring of the success of predicting market risk in investment processes, especially regarding the given estimations for the period 2010 - 2012 and the choice of the adequate methods of calculating VaR under the different market conditions (stability, moderate volatility and expressive volatility).

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Table A1. Backtesting results for historical simulation VaR with 95% confidence level of the stock indices in the period 02/01/2007 - 31/12/2007.

	HS VaR with 95% confidence level											
Stock index	HS 50	No. of days	Probability value	HS 100	No. of days	Probability value	HS 200	No. of days	Probability value	HS 250	No. of days	Probability value
SBI20	Reject	-5	0.0152	Reject	-7	0.0051	Reject	-8	0.0027	Reject	-8	0.0027
CROBEX	Reject	-7	0.0051	Reject	-3	0.0367	Reject	-5	0.0152	Reject	-6	0.0091
BELEXline	Reject	-8	0.0524	Reject	-5	0.0152	Reject	-10	0.0007	Reject	-11	0.0003
BUX	Reject	-8	0.0027	Reject	-4	0.0243	Accept	5	0.1034	Accept	5	0.1034
Unsuccessful	4			4			3			3		

Source: Author's calculations.

Table A2. Backtesting results for Delta normal VaR with 95% confidence level of the stock indices in the period 02.01.2007-31.12.2007

	Delta normal VaR with 95% confidence level											
Stock index	D 50	No. of days	Probability value	D 100	No. of days	Probability value	D 200	No. of days	Probability value	D 250	No. of days	Probability value
SBI20	Accept	1	0.1034	Accept	4	0.1053	Reject	-3	0.0027	Reject	-3	0.0027
CROBEX	Reject	-7	0.1034	Accept	4	0.1053	Accept	1	0.1034	Accept	1	0.1034
BELEXline	Reject	-2	0.0524	Reject	-1	0.0702	Accept	5	0.0891	Accept	5	0.0891
BUX	Accept	1	0.1034	Reject	-1	0.0702	Accept	5	0.0891	Accept	5	0.0891
Unsuccessful	2			2			1			1		

Source: Author's calculations.

Table A3. Backtesting results for Historical simulation VaR with 95% confidence level of the stock indices in the period 02/01/2008 - 31/12/2008.

	HS VaR with 95% confidence level											
Stock index	HS 50	No. of days	Probability value	HS 100	No. of days	Probability value	HS 200	No. of days	Probability value	HS 250	No. of days	Probability value
SBI20	Reject	-9	0.0007	Reject	-12	0.0001	Reject	-8	0.0015	Reject	-11	0.0002
CROBEX	Reject	-8	0.0015	Reject	-8	0.0015	Reject	-17	0.0000	Reject	-23	0.0000
BELEXline	Reject	-3	0.0029	Reject	-4	0.0157	Reject	-3	0.0249	Reject	-4	0.0157
BUX	Reject	-9	0.0007	Reject	-10	0.0003	Reject	-9	0.0000	Reject	-6	0.0000
Unsuccessful	4			4			4			4		

Source: Author's calculations.

Table A4. Backtesting results for Historical simulation VaR with 99% confidence level of the stock indices in the period 02/01/2007 - 31/12/2007.

	HS VaR with 99% confidence level											
Stock index	**HS 50**	**No. of days**	**Probability value**	**HS 100**	**No. of days**	**Probability value**	**HS 200**	**No. of days**	**Probability value**	**HS 250**	**No. of days**	**Probability value**
SBI20	reject	-2	0.0110	reject	-3	0.0035	reject	-7	0.0000	reject	-5	0.0002
CROBEX	reject	-5	0.0002	reject	-3	0.0035	reject	-2	0.0110	reject	-2	0.0110
BELEXline	reject	-9	0.0000	reject	-6	0.0001	reject	-2	0.0110	reject	-3	0.0035
BUX	accept	0	0.0714	reject	-2	0.0110	accept	1	0.1396	accept	1	0.1396
Unsuccessful	3			4			3			3		

Source: Author's calculations

Table A5. Backtesting results for Delta normal VaR with 99% confidence level of the stock indices in the period 02/01/2007 – 31/12/2007.

	Delta normal VaR with 99% confidence level											
Stock index	**D 50**	**No. of days**	**Probability value**	**D 100**	**No. of days**	**Probability value**	**D 200**	**No. of days**	**Probability value**	**D 250**	**No. of days**	**Probability value**
SBI20	reject	-3	0.0035	reject	-4	0.0010	reject	-6	0.0000	reject	-6	0.0002
CROBEX	reject	-5	0.0714	accept	0	0.0714	accept	0	0.0714	accept	0	0.0714
BELEXline	reject	-7	0.0000	reject	-5	0.0002	accept	1	0.1396	accept	1	0.1396
BUX	accept	0	0.0714	accept	0	0.0714	accept	1	0.1396	accept	1	0.1396
Unsuccessful	3			2			1			1		

Source: Author's calculations

Table A6. Backtesting results for Historical simulation VaR with 99% confidence level of the stock indices in the period 02/01/2008 - 31/12/2008.

	HS VaR with 99% confidence level											
Stock index	**HS 50**	**No. of days**	**Probability value**	**HS 100**	**No. of days**	**Probability value**	**HS 200**	**No. of days**	**Probability value**	**HS 250**	**No. of days**	**Probability value**
SBI20	reject	-9	0.0000	reject	-8	0.0001	reject	-7	0.0002	reject	-7	0.0002
CROBEX	reject	-6	0.0010	reject	-6	0.0010	reject	-6	0.0010	reject	-7	0.0002
BELEXline	reject	-8	0.0000	reject	-7	0.0002	reject	-6	0.0010	reject	-6	0.0010
BUX	reject	-5	0.0035	reject	-8	0.0001	reject	-10	0.0000	reject	-13	0.0000
Unsuccessful	4			4			4			4		

Source: Author's calculations

Table A7. Backtesting results for Delta normal VaR with 99% confidence level of the stock indices in the period 02/01/2008 – 31/12/2008.

	Delta normal VaR with 99% confidence level											
Stock index	D 50	No. of days	Probability value	D 100	No. of days	Probability value	D 200	No. of days	Probability value	D 250	No. of days	Probability value
SBI20	reject	-11	0.0000	reject	-16	0.0000	reject	-14	0.0002	reject	-14	0.0002
CROBEX	reject	-6	0.0002	reject	-10	0.0000	reject	-13	0.0000	reject	-13	0.0000
BELEXline	reject	-10	0.0000	reject	-11	0.0000	reject	-11	0.0000	reject	-12	0.0000
BUX	reject	-6	0.0010	reject	-11	0.0000	reject	-10	0.0000	reject	-13	0.0000
Unsuccessful	4			4			4			4		

Source: Author’s calculations

Table A8. Backtesting results for Historical simulation VaR with 99% confidence level of the stock indices in the period 02/01/2009 - 01/04/2009.

	HS VaR with 99% confidence level											
Stock index	HS 50	No. of days	Probability value	HS 100	No. of days	Probability value	HS 200	No. of days	Probability value	HS 250	No. of days	Probability value
SBI20	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256
CROBEX	accept	0	0.3398	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256
BELEXline	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256
BUX	accept	0	0.3398	accept	1	0.5256	accept	0	0.5256	accept	0	0.5256
Unsuccessful	0			0			0			0		

Source: Author’s calculations

Table A9. Backtesting results for Delta normal VaR with 99% confidence level of the stock indices in the period 02/01/2009 -01/04/2009.

	Delta normal VaR with 99% confidence level											
Stock index	D 50	No. of days	Probability value	D 100	No. of days	Probability value	D 200	No. of days	Probability value	D 250	No. of days	Probability value
SBI20	accept	0	0.3398	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256
CROBEX	accept	0	0.3398	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256
BELEXline	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256	accept	1	0.5256
BUX	accept	0	0.3398	accept	1	0.5256	accept	0	0.3398	accept	0	0.3398
Unsuccessful	0			0			0			0		

Source: Author’s calculations