Risk Measurement of Equity Markets and Private Investor Behaviour

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Abstract

Purpose of this article The aim of this paper is to evaluate and determine risk profile of equities markets and conclude consequency for private investor portfolios. There is summarized broad issue of risk measuremen with a focuse on downside risk measurement principle and giving into context with expected utility theory and loss aversion theory.
Methodology/methods The suitable statistical methods (mainly robust statistical methods) have been used for estimation of selected characteristics and ratios. There is used a computer intensive method (a bootstrap method) for estimating risk characteristics for equity markets, indicators and ratios.
Scientific aim The main scientific aim is to use a complex of more sophisticated and theoretically advanced statistical techniques and apply them on on the finding of the expected utility theory and the loss aversion theory.
Findings A main finding should be reckon a using of results of loss aversion theory applied into empirical evidence of risk profile of equity markets which led to the finding that more reliable and more suitable evaluation of risk of equity markets is downside risk and Sortino ratio from the perpective of private investor.
Conclusion Using downside risk measurement is revealing as it lays bare the "true" risk of investing in stock markets mainly for risk averse private investors. A bootstrap method with down side risk metric can evaluate risk in more appropriate way, and it is also more suitable if statistical characteristics do not fulfil a normal distribution assumption (mostly because of fat tails or outliers). And lastly in general, investors in emerging market (e.g. Visegrad´s countries) are rewarded with higher return, but if things go wrong, the damage can be severe and detrimental to performance.

Keywords: Risk, return, equity, bootstrap, robust approach, behaviour, loss aversion

JEL Classification: G17, D11

Introduction

Many private investors are looking at the issue of how to diversify their investments and optimize risk-return ratio. There are many approaches to measure risk aversion of private investors and by investor's risk profile to create a suitable portfolio. One of the classical approaches is to use meanvariance optimalization for his proposal. This approach use mean-variance analysis as the investment criterion under which investors minimize the variance of the total portfolio return by setting the portfolio expected return to a prescribed target as in the classic static case. Later private investors claim´s that because "an investor worries about underperformance rather than overperformance, semideviation is a more appropriate measure of investor's risk than variance" (Markowitz, Todd, Xu, and Yamane, 1993).

The result is perhaps the wrong balance of the investor's overall portfolio in terms of risk/return for private investor.

According that is a neccesarry to give great emphasis on investor worries about under performance it means to minimalize losses under extected returns. Therefore in this article is suggested method for analyzing equity markets indexes mostly with the focuse on "down side risk" metrics.

1 Equity Markets

There were analyzed the risk profile and some other important characteristics (e.g. return, Sharpe ratio, Sortino ratio and correlations) of equity indexes from different "trading" blocks (emerging and developed countries) in this paper. The considered equity indexes are: MSCI BRIC; CECE; EuroSTOXX 50 and MSCI AC World. A brief description of indexes follows:

- EURO STOXX 50 Price Index is the composite equity index covering 50 stocks from 12 Eurozone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain. The index is weighted by free float market capitalization. Each component's weight is capped at 10% of the index's total free float market capitalization. The free float weights are reviewed quar-terly.
- CECE Price Index is the composite equity index comprising the Czech Republic, Hungary, and Poland It is a capitalization-weighted index consisting of the Czech, Hungarian, and Polish blue chip stocks, which are members of the respective country index: CTX Czech Traded Index, HTX Hungarian Traded Index, and PTX Polish Traded Index. The index is calculated and disseminated by Wiener Börse.
- MSCI All Country World Price Index is the composite equity index covering 70 countries in the developed, emerging, and frontier markets. The index is capitalizations weighted and developed countries made approximately 90% of market capitalization of the index at the end of 1997, and at the end of 2010 only about 80%.
- MSCI BRIC Price Index is the composite equity index covering Brazil, Russia, India, and China. The index is capitalizations weighted.

All returns are quarterly price returns (without dividends) denominated in Euro. The data is available from July 1997 until December 2009. Not all emerging and frontiers markets have been included into MSCI All Country World Price Index from July 1997 onwards. As time progresses gradually, more countries were added to the index. Analyzing data from emerging countries is encountered by side effect problems:

- Data results for emerging markets are available for much shorter period then for developed ones, due that fact all equity indices started on 3rd quarter 1997.
- The question of quality and availability of the data is sometimes discussed.
- Specific regime shifts during the sample period might complicate the interpretation of empirical results over the entire sample period (e.g. some local currencies used to be fixed, but flexible exchange rate systems is applied now or vice-versa).

All these factors prevent us from drawing very strong conclusions.

2 Risk measurements

Probably the first pioneers on the field of risk measurement were Frank Knight (1921), John Maynard Keynes (1921), Richard von Mises (1928) and Andrey Komogorov (1933). During this historic period, problems of objectifications of risk measurement by using a concept of probability and applying statistical analysis were discussed. In 1952, two authors published ultimate papers for financial industry the first was H. Markowitz (1952) who identified risk as related to the varying financial outcomes and adopted the standard deviation of the residual assets as the tool for measurement of risk. He also provided a quantitative framework for measuring the portfolio risk. The second one was A. Roy (1952) who introduced the "Safety First" criterion, which meant introduction of a down-side risk measurement principle. A few years later, Markowitz (1959) gave a generalized discussion on risk, and introduced alternative measurements tools as semi-variance, expected value of loss, expected absolute deviation, probability of loss and the maximum loss. Markowitz introduced also his idea of downside-risk and suggested two types for measurement of a downside risk:

- a semivariance computed from the mean return or below-mean semivariance (SVm)
- a semivariance computed from a target return or below-target semivariance (SVt).

Both measures compute a variance using only the returns below the mean return (SVm) or below a target return (SVt). Markowitz called these measures partial or semi- variance, because only a subset of the return distribution is used see (Nawrocki, 1999).

$$SVm = \frac{1}{K}\sum_{T=1}^{K}\max\left[0,\left(E - R_T\right)\right]^2$$

$$SVt = \frac{1}{K}\sum_{T=1}^{K}\max\left[0,\left(t - R_T\right)\right]^2$$

where RT is an asset return during time period T, K is the number of observations, t is the target rate of return and E is an expected mean return of the asset's return. A maximizing function denoted as max, indicates that the formula will square the larger of two values i.e. 0 and (E – RT) or (t – RT). After proposing the semivariance measure, the classical author stayed with the variance measure because it was computationally simpler. The semivariance optimization models using a cosemivariance matrix (or semicovariance if that is your preference) require twice the number of data inputs than the variance model. With the lack of cost-effective computer power and the fact that the variance model was already mathematically very complex in these times as it belonged to the class of quadratic programs, this was a dominant consideration in practical applications until the 1980s with the advent of the microcomputer (Nawrocki, 1999). Markowitz (1987, 1991) also further developed this approach, in order to define a measure of downside risk.

3 Subjective Expected Utility Theory and Loss Aversion

The theory of individual investment decisions often assumes that financial risk is measured by the variability of yields, so that well-informed individuals can trade off this risk with the return in deciding whether to purchase the investment product. Such a risk-return trade-off is usually modelled using the well-known subjective expected utility theory (SEUT) framework, where the individual's reluctance to hold risky assets is driven by their degree of risk aversion (Eeckhoudt & Gollier, 1995).

Capon et al (1996) found that return and risk comprise only part of the decision process for individuals and that attributes other than return and risk are actively considered and weighed by investors in unit trusts: these individuals responded to perceived risk, rather than objective risk. Worzala et al (2000), and Diacon and Ennew (2001) also suggest that the principles of perceived risk may be helpful in understanding investor behaviour.

Other researchers have noted that an individual's distaste for losses is more broadly based than mere dislike of volatility; instead risk taking behaviour is characterised by an aversion to losses (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992).

Kahneman and Tversky found a theory that describes how decision-makers actually behave when confronted with choice under uncertainty. The value function shows the sharp asymmetry between the values that people put on gains and losses. This asymmetry is called loss aversion. Empirical tests indicates that losses are weighted 2-2,5 times as heavily as gains (Kahneman and Tversky, 1991).

According findings above loss aversion preferences imply that private investors who dislike downside losses will demand greater compensation, in the form of higher expected returns, for holding shares with high downside risk.

4 Applied Methods

Risk measures employed in this paper are initially estimated over the same one year period as average quarterly results. Risk meas-ures are therefore estimated over a twelve month horizon, using quarterly observations. There were obtained 54 quarterly data per each index. It is a relatively small sample to make some strong conclusions. Due to this fact, some parametrical tests were not found suitable. Therefore, there were used some robust statistical methods and bootstrap method, too. It means that statistical methods aim at constructing statistical procedures that are stable (robust) even when the underlying model is not perfectly satisfied by the available dataset. A typical example for the assumed model is the presence of outliers - observations that are very different from the rest of the data. Outliers are "bad" data in the sense that they deviate from the pattern set by the majority of data (Huber 1981, Hampel et al. 1986). Hence, they tend to obscure its generic flow and may lack explanatory and predictive power regarding the generic portion of the data. Robust models focus on the statistical properties of the bulk of the data without being distracted by outliers, while in classical models all data equally partici-pate in the analysis. Classical estimators that assign equal importance to all available data are highly sensitive to outliers. Therefore, in the presence of just a few extreme losses, classical analysis can produce arbitrarily large estimates of mean, variance, and other statistics. Bassett et al. (2004) investigate the performance of portfolio return distribution using robust and quantile-based methods, and conclude that the resulting forecasts outperform those under a conventional classical analysis. Perret-Gentil and Victoria-Feser (2005) used robust estimates for mean and the covariance matrix in the meanvariance portfolio selection problem. They showed that the robust portfolio outperforms the classical one, as the outlying observations (that account for 12.5% of the dataset) can have serious influence on portfolio selection under the classical approach.

There are used robust estimators as interquartile range and trimmed mean:

- The trimmed mean should reduce the effects of outliers on the calculated averages. This method is applied because some indexes lead to skewed distributions and there are extreme values. A 12,5% trimming level according Perret-Gentil and Victoria-Feser (2005) was used.
- The same purposes, i.e. the presence of skewed distributions and extreme values, led us to use the interquartile range (by practitioner's hint for a normal distribution is approximately equal to 1,35*standard deviation).

The bootstrap method was proposed originally proposed by Efron (1979) and it is a computationally-intensive method for estimating the distribution. The bootstrap method also helped to solve the problem of small amount of data. Therefore, there were made 5000 bootstrap samples and computed main statistics.

To use the bootstrap or any other statistical methodology effectively, one has to be aware of its limitations. The bootstrap is of value in any situation in which the sample can serve as a surrogate for the population. If the sample is not representative of the population because the sample is too small, biased, or not selected at random way, or its constituents are not independent, then the bootstrap based techniques fail. Canty et al. (2000) also list data outliers, inconsistency of the bootstrap method, incorrect re-sampling model, wrong or inappropriate choice of statistic, nonpivotal test statistics, nonlinearity of the test statistic, and discreteness of the re-sample statistic as potential sources of error.

One of the first proposed uses of the bootstrap was in providing an interval estimate for the sample median. Because the median or 50th percentile is in the center of the sample, virtually every element of the sample contributes to its determination. As we move out into the tails of a distribution, to determine the 20th percentile or the 90th, fewer and fewer elements of the sample are of assistance in making the estimate (Chernick 1999).

For a given size sample, bootstrap estimates of percentiles in the tails will always be less accurate than estimates of more centrally located percentiles. Similarly, bootstrap interval estimates for the variance of a distribution will always be less accurate than estimates of central location characteristics such as the mean or median, as the variance depends strongly on extreme values in the population. One proposed remedy is the tilted bootstrap in which, instead of classical sampling where each element of the original sample is sampled with equal probability, we weight the probabilities of selection so as to favor or discourage the selection of extreme values.

If we know something about the population distribution in advance, for example, if we know that the distribution is symmetric or that it is from certain class of distributions then we can be able to take the advantage of a parametric or semiparametric bootstrap. Recognize that in doing so, you run the risk of introducing error through an inappropriate choice of parametric framework. Problems due to the discreteness of the bootstrap statistic are usually evident from plots of bootstrap output. They can be addressed by using a smooth bootstrap as described in Davison and Hinkley (1997).

4.1 Realization

Firstly were realized an explanatory data analyses of all four indices (quarterly data), the results are shown in Table 1. According the descriptive data analysis one could say that medians are greater than means and trimmed means (12,5%) in all cases. Below mean semideviations are in all cases greater than the related standard deviations. In addition, kurtosis statistics show that the distributions have fatter tails than normally distributed variables. Next the related Box and Whiskers plots were made and results are shown in Graph 1.

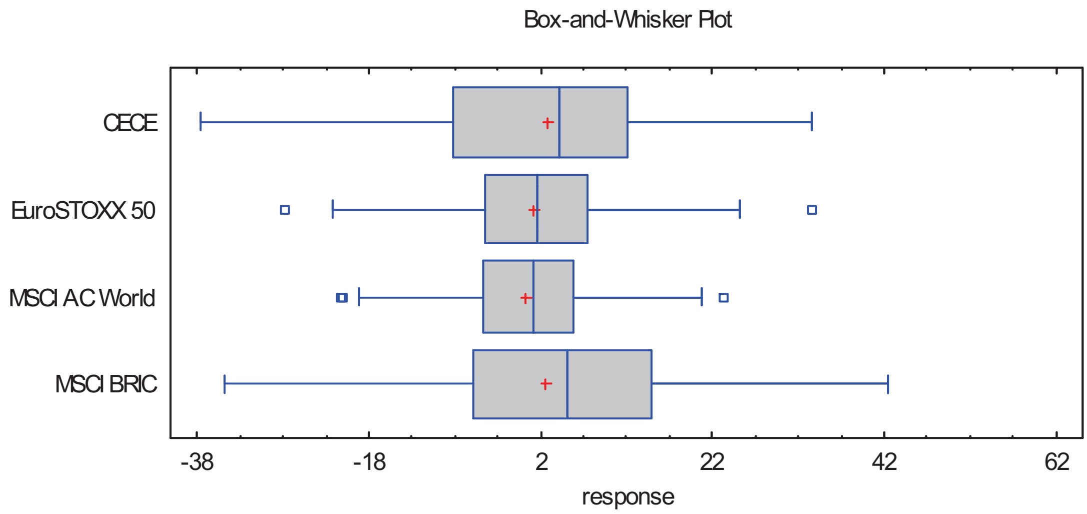
According these partial findings, the Shapiro-Wilk test of normality of distributions has been made. This test is based upon comparison of the quantiles of the fitted normal distribution to the quantiles of the data. Results are shown in Graphs 2 to 5 and Tables 2. The results for all four indices were the same and we can not reject the idea that these indexes comes from a normal distribution with at the 5% significance level. However, it was a relatively small sample of data (54 observations only per index) to make some strong conclusions.

Table 1 Quarterly summary statistics of equity indices

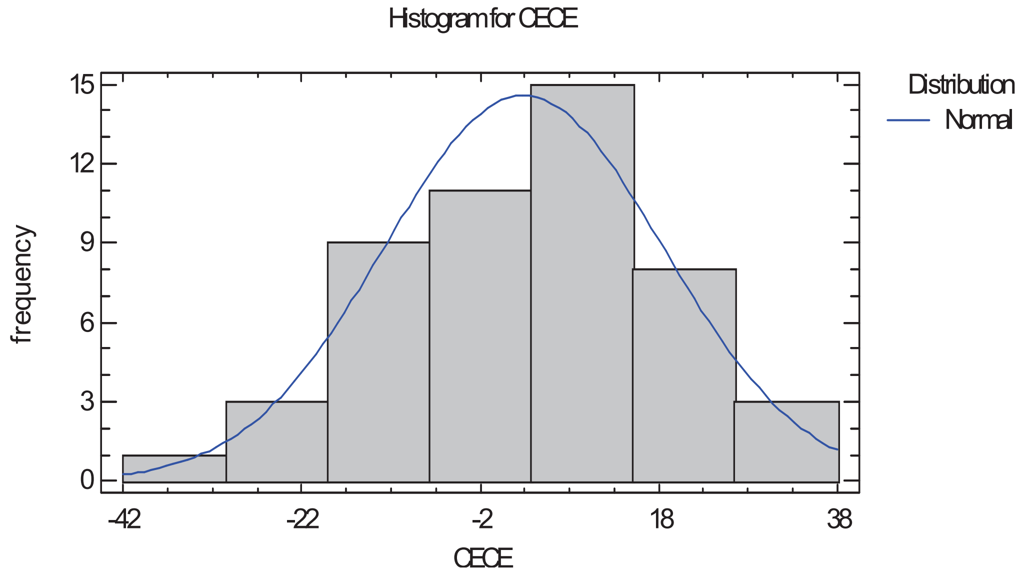
	CECE	Euro STOXX 50	MSCI AC World	MSCI BRIC
Mean	2,83	1,36	0,69	2,69
Median	4,25	1,7	1,3	5,2
12,5% Trimmed mean	3,29	1,44	0,71	2,83
Standard Deviation	15,61	12,75	10,28	17,53
Below mean semideviation	16,76	13,68	11,67	20,73
Minimum	-37,5	-27,7	-21,2	-34,8
Maximum	33,5	33,7	23,4	42,5
Interquartile range*0,75	14,73	8,67	7,72	15,46
Skewness	-0,27	-0,01	-0,27	-0,33
Kurtosis	0,026	0,27	0,07	-0,25

Note: Distributional characteristics of the quarterly period are expressed in €

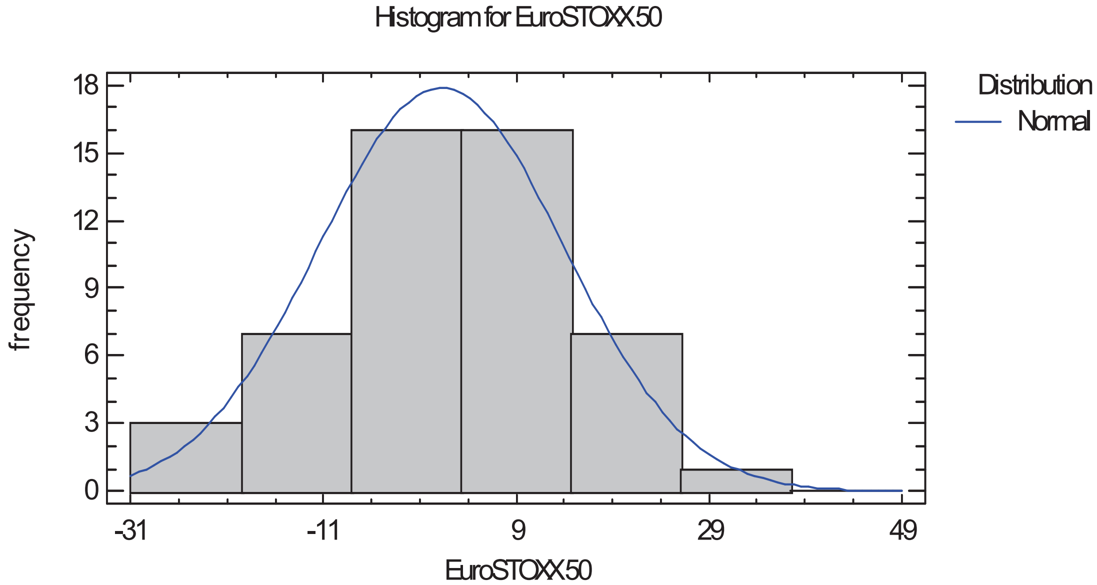
Source: Author´s calculation



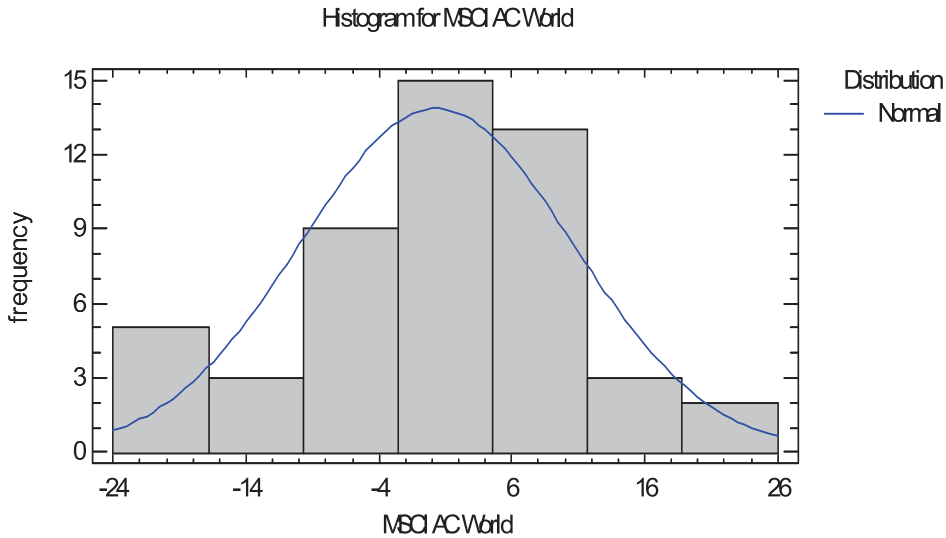
Graph 1 Box and Whiskers plot



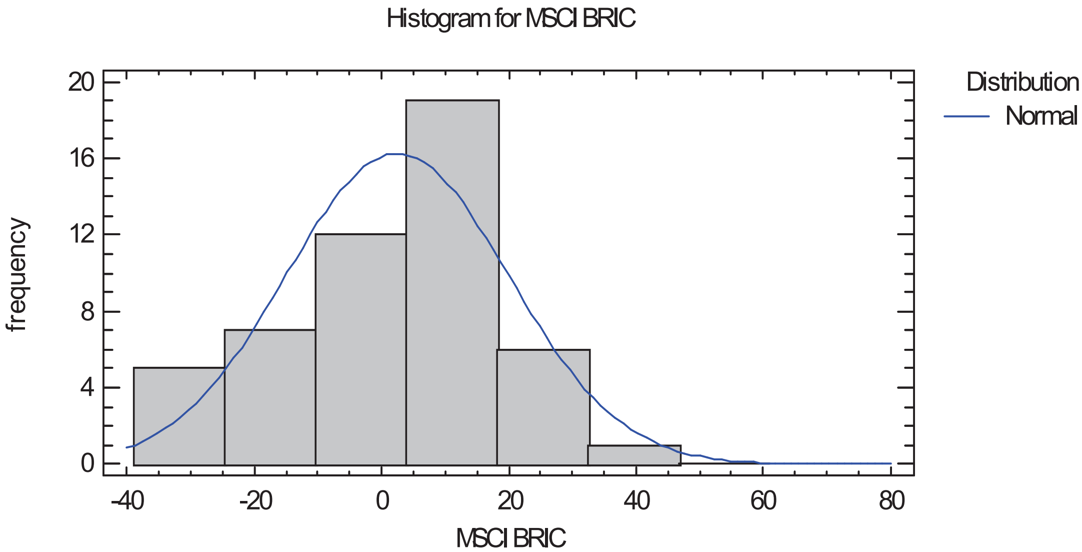
Graph 2 Histogram of CECE Index



Graph 3 Histogram of EuroSTOXX 50 Index



Graph 4 Histogram of MSCI World Index



Graph 5 Histogram of MSCI BRIC Index

Table 2 Result of the normality tests

Test Shapiro-Wilk W	Statistic	P-Value
CECE	0,984	0,876
EuroSTOXX50	0,978	0,538
MSCI AC World	0,967	0,232
MSCI Bric	0,968	0,252

Source: Author´s calculation

Within finance, investment risk is commonly defined by standard deviation, which has one major drawback. Standard deviations measure uncertainty or variability of returns but in some cases this does not match one's intuition about risk. Large positive outcomes are treated as equally risky as large negative ones. In practice, however, positive outliers should be regarded as a bonus and not as a risk. It is therefore better to look at some measure of downside risk. Next were calculated downside standard deviation, below mean deviation and Sharpe ratio and modified Sortino ratio (Sortino, Van der Meer 1991) for each index see Table 3.

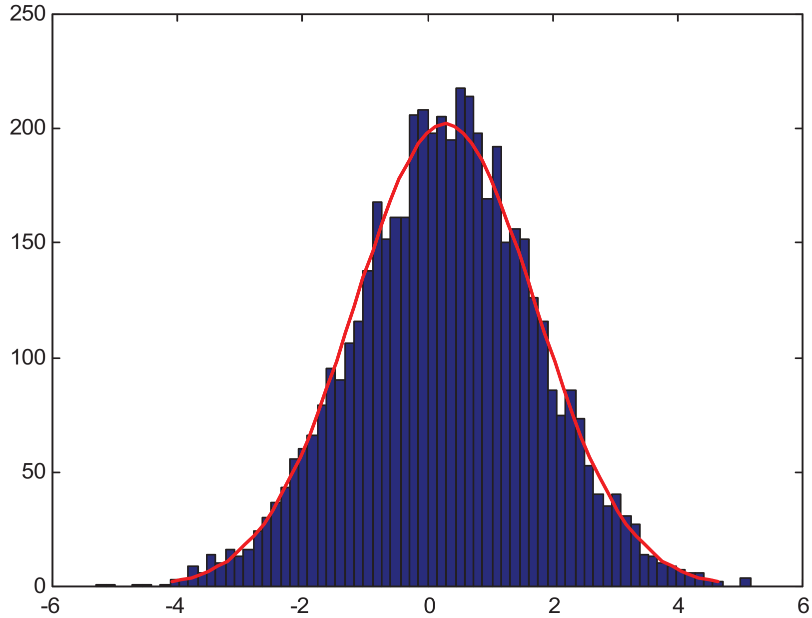
Table 3 Annulized summary statistics of equity indices

	CECE	Euro STOXX 50	MSCI AC World	MSCI BRIC
Mean*	11,32	5,44	2,76	10,76
Trimmed mean (12,5%)**	13,16	5,76	2,84	11,32
Standard deviation***	31,22	25,5	20,56	35,06
Below mean target Semideviation****	33,52	27,36	23,34	41,43
Sharpe ratio*****	0,27	0,10	-0,01	0,22
Modified Sortino ratio******	0,30	0,10	-0,01	0,20

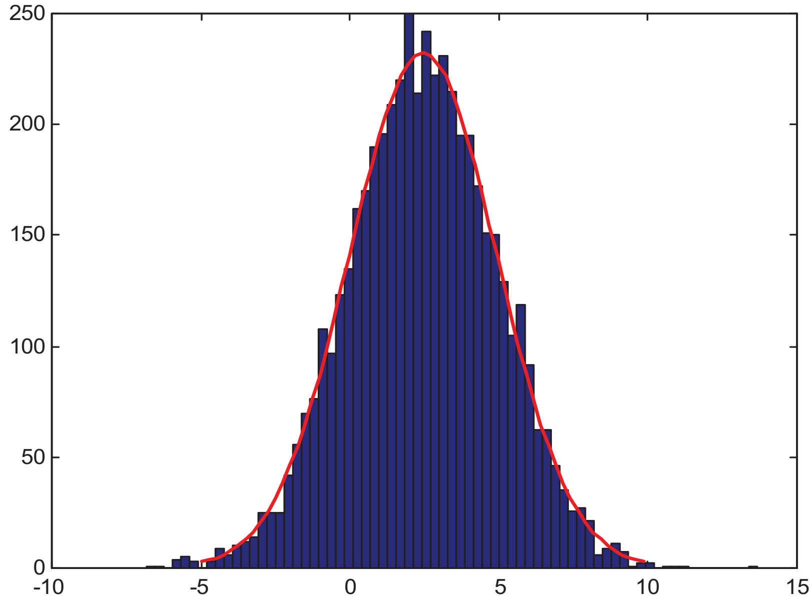
* annuals returns are calculated as quarterly values multiplied 4
** annuals returns are calculated as quarterly trimmed means values multiplied 4
*** annuals standard deviations are calculated as quarterly values multiplied 2
**** target was set as a annualised trimmed mean (12,5%)
***** average annual return = mean, risk free rate is set to 3%
******average annual return = trimmed mean (12,5%), target return is set to 3%

Memo: All statistics are annualized

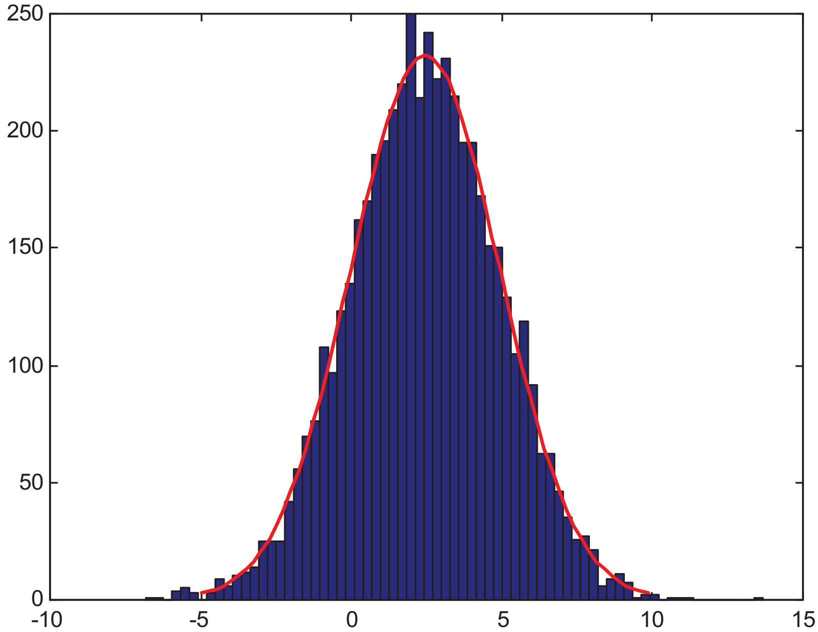
Source: Author´s calculation



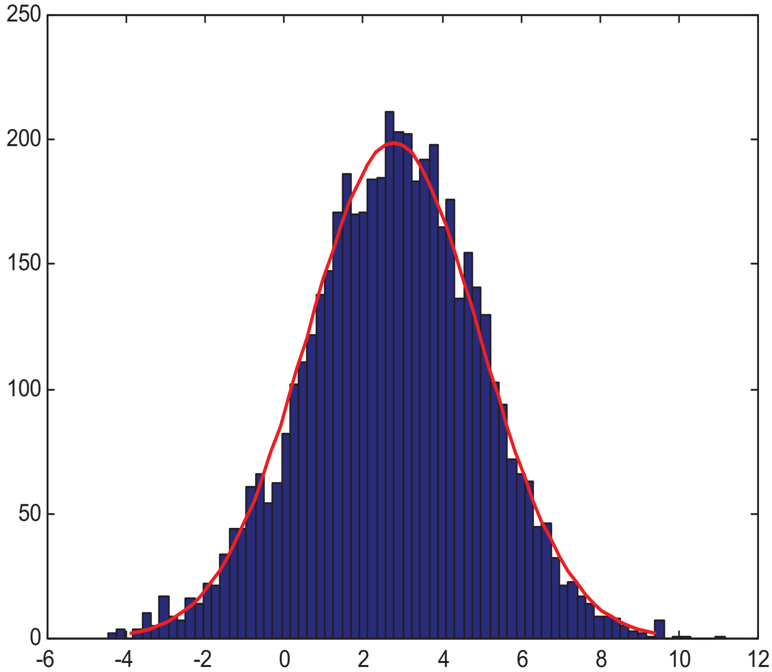
Graph 6 A bootstrap sample of MSCI AC World



Graph 7 A bootstrap sample of MSCI BRIC



Graph 8 A bootstrap sample of EUROSTOXX 50



Graph 9 A bootstrap sample of CECE

Table 4 A bootstrap characteristics

	CECE	Euro STOXX 50	MSCI AC World	MSCI BRIC
Trimmed mean (12,5%)**	12,69	5,63	2,76	11,06
Median	14,28	7,89	5,32	20,28
Below mean target semideviation	32,96	26,77	22,98	39,34
Modified Sortino ratio******	0,29	0,10	-0,01	0,20

** annuals returns are calculated as quarterly trimmed means values multiplied 4
**** target was set as a annualised trimmed mean (12,5%)
******average annual return = trimmed mean (12,5%), target return is set to 3%
*average annual return = mean, risk free rate is set to 3%

Source: Author´s calculation

5 Discussion

According obtaining result in the process of data analyzing of indexes there were find these facts:

- Three of four of indexes are largerly negatively skewned (CECE, MSCI AC World and MSCI BRIC). This findings support the idea of huge negative returns, more negative then the most positive returns therefore this equity indexes will have greater down side risk.
- Average annual return of European Blue Chip STOXX 50 TR index is close to 5% p.a., this value is very low comparing to long time average returns. The analyzing period was short and includes two deep stocks declining. Mainly this fact prevents us from drawing very strong conclusions.
- Emerging markets equity indexes (CECE, MSCI BRIC) have done very well to comparing to other two indexes according annuals returns.
- The best Sharpe ratio and modified Sortino ratio have reached CECE index. This fact is very useful for creating investments portfolios mainly for private investors from Visegrad´s countries.
- Modified Sortino ratio is a better criterium than Sharpe ratio because there is no “penalization” when the index values fluctuations are

in the value of upwards to target or mean value.

The question whether a private investor should invest into such risky equity markets as CECE or BRIC countires is not to answer without optimalization of all asset clasess in which a private investor wants to invest. It depends mainly on expected target return and his/her risk capacity connected with time horizont. There should be used an advance robust techniques with the impact on down side risk mainly for a process of portfolio optimalization.

Conclusion

There there were made explorations to measure risk aversion of private investors with „down side risk"approach in this paper. There were explorated the selected risk characteristics of important stock indexes using standard statistical techniques, robust statistical techniques and computer simulated technique a bootstrap was realized.

The results show statistically significant differences between indexes in developing countries (EuroSTOXX 50 and MSCI AC World) and indexes of emerging countries (MSCI BRIC and CECE). For deeper risk analysis there have been used robust statistical approach and computer intensive method - a bootstrap method. Using downside risk measurement is revealing as it lays bare the "true" risk of investing in stock markets mainly for risk averse private investors. A boot-strap method with down side risk metric can evaluate risk in more appropriate way, and it is also more suitable if statistical characteristics do not fulfil a normal distribution assumption (mostly because of fat tails or outliers). And lastly in general, investors in emerging market are rewarded with higher return, but if things go wrong, the damage can be severe and detrimental to performance. The main idea of the paper was to present the original combination of traditional and recent techniques (downside risk related characteristics, simulation and bootstrap) and selected real-world data (considered four indexes) and over-simplifying formulas with the impact on to give great emphasis on investor worries about under-performance it means to minimalize losses under extected returns.

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