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Value at Risk Model Used to Stock Prices Prediction

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Abstract

Radim Gottwald: **Value at Risk Model Used to Stock Prices Prediction**

The focus of the author is the Value at Risk model which is currently often adopted as the risk analysis model, particularly in banking and insurance. Following the model principle characteristics, the Value at Risk is economically interpreted. Attention is paid to the distinct features of three sub-methods: historical simulation, the Monte Carlo method and variance and covariance method. A row of empirical studies of the practical application of these methods are provided. The objective of the paper is the application of the Value at Risk model on shares from the SPAD segment of the Prague Stock Exchange between 2009 and 2011. A corresponding reliability interval, hold time, historical period and other essential parameters related to the sub-methods are gradually defined and chosen. By using historical values of stocks and shares, diverse statistical indicators are calculated. The diversified Values at Risk of the sub-methods are benchmarked against the non-diversified ones. The results show that any loss related to the non-diversified Value at Risk is always higher among the three methods than a loss related to a diversified Value at Risk. We can expect – with selected probability – a drop in the value of the portfolio which differs depending on which method is adopted based on recent share developments. The methodology is further benchmarked against other methodologies used in other papers applying the Value at Risk model. The message of this paper lies in the unique selection of applied methods, risk factors and the stock market. The methodology allows us to evaluate the risk level for investments in shares in a specific way, which will be appreciated by numerous financial entities when making an investment decision.

Key words

Risk measurement, historical simulation method, Monte Carlo method, variance covariance method

JEL: C15, E37, G32

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Introduction

Investments in financial assets are made by many entities. Any such investment entails a specific risk level. Gottwald (2008) describes the risk level as the degree of uncertainly that the financial instrument selected will not make the profit expected by the investor. He also divides risks based on diverse criteria and mentions possible risk reduction options. One of the possibilities how to calculate the risk level for investments in financial assets is the adoption of the Value at Risk model.

The focus of this paper is the Value at Risk model being the risk analysis model frequently adopted mostly in banking and insurance. The use of the Value at Risk model has been studied by many economists who present the results of their empirical research focused on the application of the Value at Risk model in practice – not only in the banking sector. The market risk measurement and management has therefore received new knowledge which was benchmarked against that from other papers.

The Value at Risk model is a relatively simple and efficient instrument for measuring and controlling market risk for different portfolios. It is based on the assumption that future risk can be deduced from historical values, which clearly shows it was inspired by the modern portfolio theory. The statistical analysis of risk measurement and management provides an unbiased and independent evaluation of the risk size. The Value at Risk expresses the maximum potential loss calculated with a certain probability during a hold time determined for the portfolio of a financial entity over a specific historical period in case of adverse market changes. When adopting the Value at Risk model, first the reliability interval, hold time and historical period are chosen. The Value at Risk value is in fact a one-sided quantile (e.g. 95%) of profit distribution and portfolio losses during a hold time (e.g. one day) determined based on selected historical period (e.g. three years). It is the maximum potential loss which should not be exceeded during the following hold time with selected probability.

Back testing can be applied to the Value at Risk model in which the results of the Value at Risk model are benchmarked against actual future results. In the testing, anticipated portfolio losses are benchmarked against actual portfolio losses to find out how accurate the model is, i.e. to what extent the results calculated by the Value at Risk model match reality. Also, stress testing in which the Value at Risk model is tested on a portfolio for a certain stress scenario for the development of stocks and shares, commodity prices, exchange rates and interest rates can be done. These stress tests can reveal future stress situations to which banks can be exposed e.g. during an economic crisis, when the stock market crashes, in wars, etc.

The Value at Risk model was first adopted by big US banks in 1980s in connection with the great boom of derivative trading which opened new opportunities for risk management. In 1996 the Basel Committee for Bank Supervision enabled certain banks to deviate from standardised procedures and measure their exposure to market risk with the use of their own models. Since that year banks in the European Union and since 1998 in the USA can adopt their own Value at Risk calculation practices and influence their own capital requirements. In the context of the implications of the financial crisis, great emphasis has been laid on the adoption of quality mechanisms in risk management in banking over the past five years. The Value at Risk model is currently wide-spread in the banking industry in connection with the determination of capital adequacy of a certain bank. The Value at Risk model allows a more flexible form of banking supervision. Besides the Basel Committee for Bank Supervision, also central banks and financial institutions are dealing with this bank risk management model.

The objective of this paper is the application of this model on real data from a selected financial market. The model allows a closer identification of the market, which will be appreciated by a number of entities operating on the financial market. Potential investors can estimate the future market development in the short term thanks to past data. They can predict a potential loss of an investment in stocks and shares, which ensures better orientation on the market.

For an accurate definition of the benefits of this paper and its place within systematic market risk measurements and management, several specifics through which this paper is different from other papers need to be mentioned. Three sub-methods are benchmarked in the paper: historical simulation method, the Monte Carlo method and the variance and covariance method. In other papers one single method and/or other sub-methods are applied and then benchmarked. Shares are chosen as risk factors. Risk factors in other papers are in the form of obligations, stock portfolios, stock indices, exchange rates, interest rates announced by the central bank, commodity values, options and other types of financial derivatives. In this paper the Value at Risk model is applied to the Czech stock market – specifically to the Prague Stock Exchange. Many other papers are applied mostly to the US financial market and/or some other significant world stock market. The Value at Risk model is adopted for market risk measurement in this paper. The models used in many other papers allow the measurement of only some types of market risks including interest, stock, loan, currency, commodity risks and other types of risk. Models of the gap and duration gap type therefore do not follow a comprehensive market risk approach. Furthermore, unlike many other models, the Value at Risk model takes into account possible correlation between different types of market risk and risk factors, and between risk factors themselves. These are the specifics thanks to which this paper is useful. A number of financial entities will appreciate the possibility to assess the risk level for their investments in stocks and shares when making an investment decision and adopt this methodology.

1 Theoretical Background

Three sub-methods are adopted in the Value at Risk model: historical simulation method, the Monte Carlo method and the variance and covariance method. Numerous factors need to be taken into account then making the decision which of the three methods shall be adopted. Each of these methods is specific and rests upon different assumptions. The methods differ in the way input data is processed – particularly in whether the parameters of the probability distribution of risk factors of the correlation type, volatility type, etc. shall be estimated, in whether the method can be adopted for non-linear relationships between the portfolio value and risk factor level, i.e. to instruments with non-linear value progress, e.g. non-linear option portfolios, in whether the method requires demanding calculations, whether specialised software is required and whether random figures must be used. The Monte Carlo method is regarded as the most precise one provided the stochastic model was correctly chosen and is suitable rather for institutions with extensive trade portfolios for which high model precision is essential. The calculation accuracy for Value at Risk in the Monte Carlo method is determined by the quality of the random figure generator, by the selection of the rational calculation algorithm and accuracy verification of the Value at Risk calculated.

1.1 Historical Simulation Method

In this non-parametric method, time lines of actual historical risk factor values over a selected historical period are used. Weights are assigned to risk factors. Diverse financial assets can be chosen as risk factors. Value at Risk and expected shortfall for Standard&Poor´s 500 and CAC 40 Stock exchange indexes during the 2008 financial crisis is measured by Kourouma, Dupre, Sanfilippo and Taramasco (2010). They consider 1 day, 5 days and 10 days time horizont. In order to evaluate the Value at Risk approaches, Lin and Chien (2002) collect data from the New York S&P 500, the London Times FTSE 100 and the Frankfurt Index using data period 1990-2001. They incorporate a generalized error distribution model into the historical simulation. Zenti and Pallotta (2001) use several indices to test the accuracy of the different Value at Risk methods analysed. They use historical simulation and bootstrap approach in risk analysis for asset managers. Portfolios of securities can be also chosen as risk factors. Multi horizon portfolio insurance model is analysed by Stulajter (2010). It enables explicit definition of investment horizons in regular opened-end fund framework that utilizes popular portfolio insurance strategy based on Value at Risk. The historical simulation based on US financial data is used. Some authors choose exchange rates as risk factors. Fajardo, Farias and Ornelas (2005) analyze the use of generalized hyperbolic distributions to model the US Dollar/Brazilian Real exchange rate in a way to produce more accurate Value at Risk measurements. Several methods are compared, concretely historical simulation, RiskMetrics, unconditional normal, generalized hyperbolic, normal inverse Gaussian and hyperbolic, and GARCH models using normal, generalized hyperbolic, hyperbolic and normal inverse Gaussian. The comparison of various stress tests for foreign exchange positions, based on hypothetical scenarios, across a number of Value at Risk methods is described by Basu (2009). Harris (2004) compares the reduction in 99% Value at Risk with reduction in standard deviation for 13 cross-hedged currency portfolios using both out-of-sample and in-sample approaches. Minimum-Value at Risk hedging strategy that minimises the historical simulation Value at Risk of the hedge portfolio is proposed. To choose risk factors, commodity prices are also used. Value at Risk for daily electricity spot prices with use of extreme value theory is measured by Chan and Gray (2006). Some authors calculate with risk factors in form of hedge funds. Weng and Trueck (2009) apply Value at Risk to Asia-focused hedge funds. They attempt to identify risk factors for these funds through modified style analysis technique. Through suggested empirical model, Lhabitant (2001) analyze the investment style of individual hedge funds and funds of funds. The approach is based on historical simulation, the factor push approach used in stress testing and others.

1.2 Monte Carlo Method

Different financial assets can be chosen as risk factors as well when adopting this stochastic method. Beveridge and Joshi (2010) use Monte Carlo simulation to pricing of convertible bonds. Similarly, to value convertible bonds, Wilde and Kind (2005) apply Monte Carlo simulation-based pricing method. Stock Exchange indexes are sometimes used as risk factors. Using various tests, Colucci and Brandolini (2011) present results on both Value at Risk 5% and Value at Risk 1% on one day horizon for the Monte Carlo filtered bootstrap and historical simulation for the following indices: Standard&Poors 500, MSCI United Kingdom, MSCI France, MSCI Canada, MSCI Emerging Markets, Topix, Dax, Italy Comit Globale and RJ/CRB. Portfolios of securities can be also chosen as risk factors. Capriotti (2007) describe least squares importance sampling strategy for Monte Carlo simulation security pricing. Using several numerical examples, he shows that this strategy provides efficiency gains comparable to the state of the art techniques, when the latter are known to perform well. The performance of Monte Carlo simulations for optimal portfolios is analysed by Detemple, Garcia and Rindisbacher (2000). This performance in the numerical implementation of portfolio rules derived on the basis of probabilistic arguments is improved. Monte Carlo simulation portfolio optimization for general investor risk-return objectives and arbitrary return distributions is realized by Shaw (2010). To solve portfolio investment problems, he uses Monte Carlo simulation sampling of random portfolios. Shaw (2011) further presents Monte Carlo simulation approach for long-only and bounded short portfolios with optional robustness and a simplified approach to covariance matching. Some authors use interest rates announced by central banks as risk factors. Tracking of the US interest rate by sequential Monte Carlo simulation is realized by Lombardi and Sgherri (2007). They attempt a real-time evaluation of the US monetary policy stance while ensuring consistency between the specification of price adjustments and the evolution of the economy under flexible prices. Monte Carlo method can be applied to various types of financial derivatives. Marshall (2008) builds a Monte Carlo simulator to value a plain vanilla put, plain vanilla call and an option written on more than one underlying asset. Potters, Bouchaud and Sestovic (2000) price low variance financial derivative with objective probabilities. This method allows to determine simultaneously the optimal hedge and it can be used to price a large class of exotic options. Long-maturity equity derivatives are priced by Monte Carlo simluation by Chen, Grzelak and Oosterlee (2011). Credit derivatives are priced under factor copula models by Curran (2006). Beveridge and Joshi (2009) use Monte Carlo simulation to obtain rapid and tight bounds for Bermudan exotic derivatives. Options belong among risk factors used within application of Monte Carlo method. To valuate real options, Gamba (2003) use Monte Carlo simulation. Similarly, to valuate American options by Monte Carlo simulation, Rasmussen (2002) samples control variates at the exercise time of the American option rather than at expiry, which would be the case for the corresponding European option valuation. Gobet (2008) focuses on valuation of barrier options and related exotic options by Monte Carlo simulation. To evaluate pension funds, Monte Carlo method is also used. Using Monte Carlo simulation, Joshi and Pitt (2010) describe model for a defined benefit pension scheme and use adjoint methods to illustrate the sensitivity of fund valuation results to key inputs such as interest rates, mortality rates and levels of salary rate inflation.

1.3 Variance and Covariance Method

Like in the above methods, different financial assets are chosen as risk factors in this parametric method (often labelled as "analytical"). Risk factors can constitute stock portfolios. Dave and Stahl (1997) focuse on the accuracy of Value at Risk estimates based on the variance covariance approach. They use models for forecasting losses in relation to a portfolio of risk factors as well as losses in relation to positions held against individual risk factors. Implementing Value at Risk for Indian banking system, Nath and Samanta (2003) price portfolios as well as bonds. They use zero-coupon yield curve and adopt three categories of Value at Risk methods, concretely historical simulation, variance covariance including RiskMetric and tail-index based method. The systematic relationship between correlation mis-estimation and the corresponding Value at Risk mis-calculation is examined by Skintzi, Skiadopoulos and Refenes (2005). They employ Monte Carlo simulation and variance covariance method. Variance and covariance method can be applied to exchange rates. Focusing on forex market in India, Nath and Reddy (2003) adopt three categories of Value at Risk methods, concretely historical simulation, variance covariance including RiskMetric and tail-index based method. Ferreira and Lopez (2005) evaluate interest rate covariance models between national interest rates and accompanying exchange rates. Based on results, covariance matrix forecasts generated by models incorporating interest-rate level volatility effects perform best with respect to statistical loss functions.

2 Methodology

Shares were chosen as the risk factors on which the method can be applied. The methods are applied to the Prague Stock Exchange – specifically to its SPAD segment, intended for trading the most prestigious stocks and shares offered on this stock exchange. The shares of AAA, CETV, ČEZ, ECM, ERSTE BANK, KOMERČNÍ BANKA, NWR, ORCO, PEGAS, PHILIP MORRIS, TELEFÓNICA, UNIPETROL and VIG were chosen in this segment. The shares are numbered from 1 to 13 according to this order. The shares of FORTUNA and KITD from the SPAD segment were not included, because they were first traded only after the start of the historical period. The historical period for which data was collected is from January 2, 2009 to December 30, 2011 and the Value at Risk was determined as of 30 December, 2011. One day was selected as the hold time. Input data is comprised of a time line with a one-day periodicity, i.e. these are daily share prices. A 95% reliability interval was selected. The Value at Risk is calculated with the probability in this amount. The source of data is the database of Patria Finance, a.s. The input data – historical share prices – necessary for the implementation of the empirical analysis was obtained through Patria Online, a.s. (2012). These are closing share prices reported always in CZK. The weight of the different shares in the portfolio is calculated based on share prices as of 30 December, 2011.

3 Results

3.1 Joint Input Data for the Adoption of All Three Methods

This data is shown in Table 6 in the appendix. The weight of the different shares in the portfolio is calculated based on share prices as of 30 December, 2011. One piece is always taken for each share. The indicators related to historical share prices include the standard deviation, mean value and variance coefficient. Also, historical share prices, being in fact the absolute historical risk factor values, and changes to historical share prices, being in fact the relative historical risk factor values, are reported. This determines the volatility of the shares in the portfolio.

3.2 Application of the Historical Simulation Method

Table 1 shows share conversion values which are in fact the current values of risk factors. These values are calculated as the totals of share prices as of 30 December, 2011 and of changes to share prices.

Table 1: Share conversion values by the historical simulation method

Date	1	2	3	4	5	6	7	8	9	10	11	12	13	Sum
30.12.2011	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
29.12.2011	-0,60	-1,17	3,98	0,00	-1,00	-22,15	-1,06	-1,44	-1,00	-24,05	-1,10	-0,53	-22,41	-72,54
28.12.2011	0,24	1,21	-10,08	0,00	1,00	-25,36	-0,40	-1,49	-4,35	-56,36	-2,42	0,53	20,73	-76,75
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
6.1.2009	0,31	9,33	22,48	0,15	12,13	130,40	0,31	-3,60	6,50	339,89	8,28	1,74	-0,50	527,44
5.1.2009	-0,46	-3,24	-28,90	-0,71	-5,76	11,81	0,89	-0,54	-18,76	238,74	-13,56	-1,46	18,16	196,21
2.1.2009	0,49	-8,14	-11,73	0,96	-0,82	-51,25	2,08	-14,36	3,26	97,88	-11,07	-0,29	-8,68	-1,68

Source: own calculations with use of Patria Online, a.s. (2012)

The more stable the price of any of the shares over a certain period, the closer its converted value to zero. While positive values indicate growing share prices from the previous day to the day in question, negative values indicate a drop. A comprehensive development shown in the last column of Table 1, i.e. summary values of all selected shares from 2 January 2009 to 30 December 2011, can be also found in Figure 1.

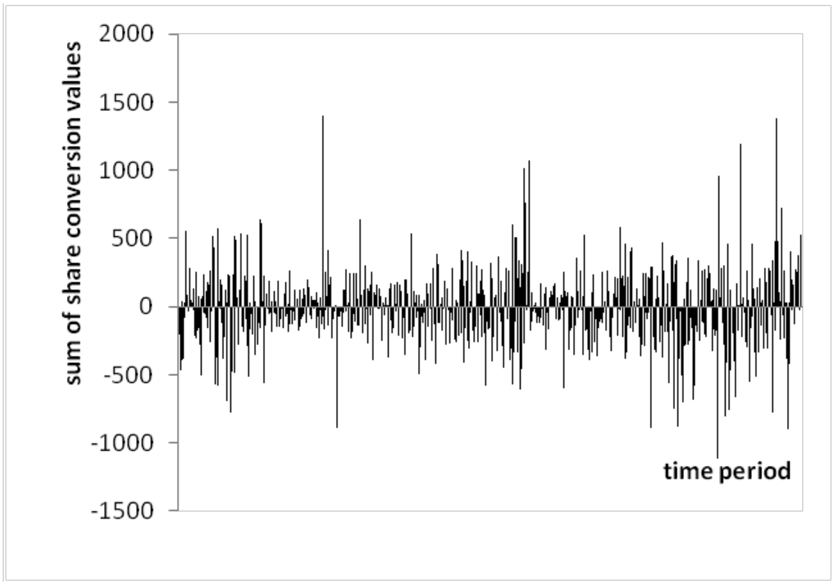

Figure 1: The progress of sum of share conversion values by the historical simulation method during 2009-2011 (Source: own calculations with use of Patria Online, a.s. (2012))

The fluctuation of values in the figure reflects the fluctuation of shares from selected market. The 5% percentile (one-sided quantile), amounting to -412.26, was calculated from these values in respect of the 95% reliability interval selected. This is a diversified Value at Risk.

Table 2 shows the 5% percentile, calculated extra for each share from converted share prices.

Table 2: 5 % percentil by the historical simulation method

Indicator	1	2	3	4	5	6	7	8	9	10	11	12	13
Percentil 5 %	-0,62	-7,68	-20,10	-1,23	-18,16	-138,06	-6,42	-5,18	-11,97	-340,15	-8,24	-6,11	-27,54

Source: own calculations with use of Patria Online, a.s. (2012)

The total, -591.46 is calculated from the values from Table 2. This is a non-diversified Value at Risk. The table shows the portions of shares in the non-diversified Value at Risk. We need to be aware of the fact that the amount of the percentile of a certain share is affected not only by the price fluctuation of this share, but also by the share price as of 30 December, 2011 in absolute terms.

3.3 Application of the Monte Carlo Method

Standard matrix operations within linear algebra are adopted because of the use of the matrices for the Value at Risk calculation.

At the first, the covariance matrix is calculated based on changes to historical share prices. Standard distribution is applied for the type of probability distribution. Also the number of simulations and form of value simulation are chosen. A total of 10 000 simulations are implemented by using the NtRand 3.2 software from Numerical Technologies. This software enables to simulate share prices and other variables.

Table 3 shows the simulation of share prices calculated from the covariance matrix.

Table 3: Simulation of share prices by the Monte Carlo method

Simulation number	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0,02	-0,03	0,00	0,00	-0,01	0,00	-0,04	0,02	0,00	-0,03	0,00	0,01	-0,03
2	-0,02	0,03	0,00	0,00	0,01	0,00	0,04	-0,02	0,00	0,03	0,00	-0,01	0,03
3	0,02	0,02	0,00	0,03	-0,01	0,03	-0,01	0,01	0,00	-0,02	-0,01	0,01	0,00
…	…	…	…	…	…	…	…	…	…	…	…	…	…
9 998	-0,06	-0,04	-0,02	0,00	-0,05	-0,06	-0,02	-0,03	0,01	-0,01	-0,01	-0,02	-0,06
9 999	-0,02	0,00	-0,01	-0,06	0,00	0,03	-0,03	0,03	-0,01	0,01	-0,02	0,02	-0,01
10 000	0,02	0,00	0,01	0,07	0,00	-0,03	0,03	-0,03	0,00	-0,01	0,02	-0,02	0,01

Source: own calculations with use of Patria Online, a.s. (2012)

In this table, the hypothetical share price is calculated for each share. Thanks to the high number of simulations, this is more detailed than the actual value progress of the respective share presented in

Table 1. Also, converted simulations of share prices – i.e. the totals of share prices as of 30 December, 2011 and share price simulations – are calculated. From the total of converted share price simulations a 5% percentile, amounting to -457.15, is calculated. This is a diversified Value at Risk. Table 4 shows the 5% percentile, calculated extra for each share from converted share price simulations.

Table 4: 5 % percentil by the Monte Carlo method

Indicator	1	2	3	4	5	6	7	8	9	10	11	12	13
Percentil 5 %	-1,00	-8,48	-20,19	-1,50	-19,25	-138,55	-7,34	-5,68	-13,02	-359,88	-8,48	-5,68	-32,13

Source: own calculations with use of Patria Online, a.s. (2012)

The total, -621.20 is calculated from the values from Table 4. This is a non-diversified Value at Risk. The table shows the portions of shares in the non-diversified Value at Risk. Also here, the amount of the percentile of a certain share is affected both by the fluctuation of that share and the share price as of 30 December, 2011 in absolute terms.

3.4 Application of the Variance and Covariance Method

Firstly, the standard deviations are calculated based on changes to historical share prices. Then, the C matrix – i.e. correlation matrix – is calculated from historical share prices. Standard distribution is applied for the type of probability distribution. Furthermore, the V matrix, i.e. diagonal volatility matrix, is calculated by taking the totals of standard deviations and value 1.64. The value 1.64 is the standard, non-normalised distribution for the 95% reliability interval. Also, the VC matrix, VCV matrix, i.e. variance and covariance matrix, and the VCVW matrix are calculated. This is a column vector. The W matrix is a column vector, the values of which are comprised of share prices as of 30 December, 2011. This weight vector W contains cash flow values. The W^TVCVW is calculated as well. The W^T matrix is a row vector, the values of which are comprised of share prices as of 30 December, 2011. The W^TVCVW matrix is made only of figure 250 410.36, which is the second power of the diversified Value at Risk. After extraction, the diversified Value at Risk, amounting to -500.41, is calculated. The negative value is selected by taking into account the fact that the Value at Risk expresses the loss, not the profit.

Table 5 shows the component and individual Value at Risk matrix. The component Value at Risk matrix stated in the first line is calculated as the total of the VCVW and W matrices, subsequently diversified by the Value at Risk amounting to -500.41. This is a column vector (values are kept in a line).

Table 5: The component and individual value matrix by the variance and kovariance method

Share number	1	2	3	4	5	6	7	8	9	10	11	12	13
The first line	0,80	1,68	4,45	-0,71	12,72	118,78	5,45	0,61	11,54	321,28	-1,34	3,83	21,34
The second line	0,98	8,59	20,30	1,57	19,07	135,24	7,15	5,63	12,60	346,27	8,60	5,63	31,55

Source: own calculations with use of Patria Online, a.s. (2012)

From the values in the first line of Table 5 the total is calculated and makes 500.41. The diversified Value at Risk is a figure opposite to this figure, i.e. -500.41 as already calculated before. The table shows the portions of shares in the diversified Value at Risk. The individual Value at Risk matrix shown in the second line is calculated as the total of the W^T and V matrices. It is a row vector. The total is calculated from the values in the second line of the table and makes 603.18. The non-diversified Value at Risk is a figure opposite to this figure, i.e. -603.18. The table shows the portions of shares in the non-diversified Value at Risk. It is also clear to what extent the estimations of the diversified and non-diversified Value at Risk differ for each share. For the sake of better transparency, the share of non-diversified and diversified Value at Risk for the different shares, as represented in the rows of Table 5, is shown in Figure 2.

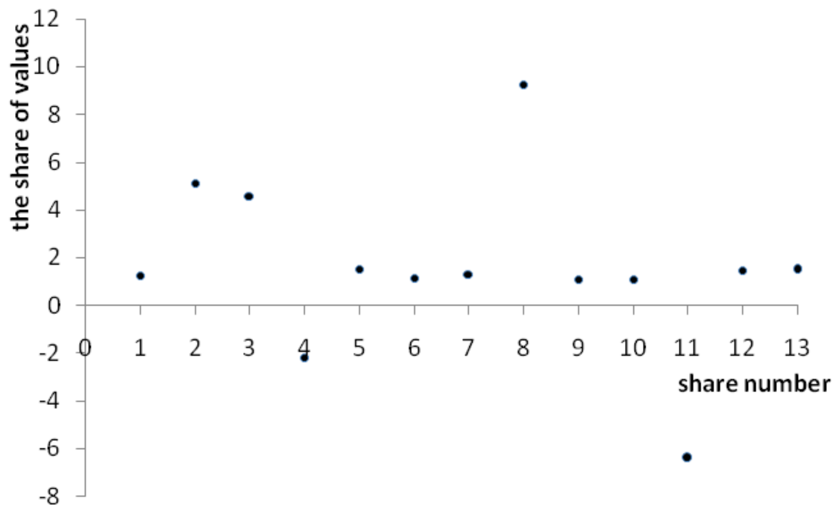

Figure 2: The share of non-diversified and diversified Value at Risk for the different shares (Source: own calculations with use of Patria Online, a.s. (2012))

It is apparent from the figure what impact the consideration of correlations between shares has on the calculation of the Value at Risk. They are not considered for the non-diversified Value at Risk, but they are considered for the diversified Value at Risk.

Discussion

Regarding the economic interpretation of the results, it needs to be described what exactly the Value at Risk stands for. In this case it expresses the maximum potential loss calculated with a 95% probability during the following day, determined based on the period from 2 January, 2009 to 30 December, 2011, which the financial entity can have in its portfolio in case of adverse market changes. Losses for share portfolios calculated by these methods can be interpreted as probable drops in portfolio values during the next period. For investors, a lower rather than higher Value at Risk is more acceptable.

The Value at Risk calculated can be benchmarked. The methods differ from each other in the way the input data is processes, i.e. in the principle for Value at Risk calculation. To be specific, the thing is which method has been adopted and whether this is a diversified or non-diversified Value at Risk.

For the calculation of the non-diversified Value at Risk, correlation between shares is not taken into account. The application of the three methods brings these results: -591.46 for the historical simulation method, -621.20 for the Monte Carlo method and -603.18 for the variance and covariance method. For the calculation of the diversified Value at Risk, correlation between shares is taken into account. The application of the three methods brings these results: -412.26 for the historical simulation method, -457.51 for the Monte Carlo method and -500.41 for the variance and covariance method. The loss related to the non-diversified Value at Risk is always higher among the three methods than a loss related to a diversified Value at Risk. The results are evidence that – with selected probability – a drop in the value of the portfolio which differs depending on which method is adopted can be expected based on the recent share development.

The methodology adopted in this paper can be benchmarked against those adopted in other papers which apply the Value at Risk model by using shares as risk factors, no matter if independently or combined with other financial assets. This paper applied the historical simulation, Monte Carlo and variance and covariance methods. The methods were applied to shares from the SPAD segment of the Prague Stock Exchange between 2009 and 2011. A 95% reliability interval was selected. Diversified and non-diversified values at risk are calculated. Angelidis and Benos (2005) apply the historical simulation and variance and covariance methods. The methods are adopted for shares from the Greek stock market, share portfolios and the Athens stock index between 1991 and 2003. Reliability intervals of 97.5% and 99% are used. Certain criteria were selected to measure the accuracy of the models adopted. Richardson, Boudoukh and Whitelaw (1997) apply the historical simulation and variance and covariance methods. The methods are applied to shares included in the stock index of Standard&Poor´s and other financial assets from 1991 to 1997. Reliability intervals of 95 % and 99% are used. A new methodology for measuring the Value at Risk is created by combining the methodologies adopted within the historical simulation and variance and covariance approaches. Angelidis, Benos and Degiannakis (2005) apply the historical simulation, variance and covariance and semi-parametric methods. The methods are applied to two portfolios included in the Dow Jones Euro Stoxx index from 1987 to 2005. Reliability intervals of 97.5 % and 99% are used. Also the statistical significance of the differences between these methods is investigated. Lee and Binh (2009) apply the historical simulation method and the Simple Moving Average (SMA) model, the Exponentially Weighted Moving Average (EWMA) model, the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model with a normal distribution, the GARCH model with a t-distribution, the Constant Conditional Correlation (CCC) model, the Dynamic Conditional Correlation (DCC) model, and the Orthogonal GARCH (O-GARCH) model. The methods are applied to share portfolios from the Korean stock market between 1991 and 2007. Reliability intervals of 99 % and 99.5 % are used. Also the accuracy of estimated values at risk for the different methods is investigated. Skiadopoulos, Lambadiaris, Papadopoulou and Zoulis (2003) apply the historical simulation and Monte Carlo methods. The methods are applied to shares and bonds of the Greek capital market from 2000 to 2002. Reliability intervals of 95 % and 99 % are used. The results of share portfolios are benchmarked against those of bond portfolios. Giovanis (2008) applies the Monte Carlo method, the GARCH process method and the wavelets analysis. The methods are applied to shares of the Greek stock market between 1997 and 2008. An algorithm for the prediction of share profits is created.

Further research in this area can go in several directions. Values at risk calculated by the three methods in question can be benchmarked not only against each other, but also against the results which can be reached if the value of some of the characteristics changes. The characteristics used for these methods include the reliability interval, hold time, historical period and portfolio structure and values. The values of characteristics can be therefore changed. There are numerous situations when the Value at Risk model can be applied. It is generally adopted for risk analyses, finding optimum portfolio values, evaluating financial derivatives including options, evaluating investments and for hedging techniques. The Value at Risk model can be implemented by banks, insurance companies, pension funds, investment funds and non-financial institutions, e.g. businesses. In the insurance sector the Value at Risk measures the fundamental risk for the assets researched. In funds, portfolios targeting a specific Value at Risk in the long run can be traded. As far as banks are concerned, we can observe the impact of the Value at Risk model on the banks' capital adequacy, but only some banks currently hold major trading portfolios and only some of them adopt the Value at Risk model. The market risk management for banks however keeps developing.

Conclusions

The Value at Risk belongs to models adopted for market risk measurement and management. This model is also in the centre of attention of the author of this paper. Following a theoretical definition of the model, it is adopted for real data. Specifically, three sub-methods are applied to the Prague Stock Exchange. The values calculated indicate maximum potential losses during the day following 30 December 2011, counted with a 95% probability, for the portfolio of a financial entity in case of adverse market changes. Historical share prices from 2 January 2009 to 30 December 2011 were used. Based on the results, it can be generally noted that this paper as well as other papers allow certain variability in calculated estimations for the calculation of the Value at Risk by using the different methods. This variability is caused by the different principle these methods are based on. Other factors affecting the Value at Risk calculated and those that can be understood as the specifics differentiating this paper from other papers include risk factors, geographical definition of the market from which the data was taken, selected historical period, hold time, reliability interval and other characteristics implemented on statistical data processing for the different methods. By using the Value at Risk model, this paper presents a way of market risk measurement under specific conditions, not adopted so far. Investors can perceive this risk measurement of most shares traded on the Prague Stock Exchange as an add-on to the many analyses investigating the performance and liquidity measurements for these shares traded on this stock exchange.

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Appendix

Table 6 shows joint input data for the adoption of all three methods.

Table 6: Input data

Share number	1	2	3	4	5	6	7	8	9	10	11	12	13
Share price 30.12.2011	17,88	127,95	786,00	25,51	347,00	3330,00	135,79	85,42	457,00	12580,00	383,10	171,00	799,90
Weight	0,09%	0,66%	4,08%	0,13%	1,80%	17,30%	0,71%	0,44%	2,37%	65,36%	1,99%	0,89%	4,16%
Standard deviation	5,60	128,30	72,65	119,12	191,77	653,79	67,88	41,81	63,84	1715,67	25,71	30,83	134,44
Mean	16,65	381,36	840,09	181,67	664,83	3546,76	182,65	173,47	412,67	8928,16	417,00	163,92	866,79
Variance coefficient	0,34	0,34	0,09	0,66	0,29	0,18	0,37	0,24	0,15	0,19	0,06	0,19	0,16
Share price 30.12.2011	17,88	127,95	786,00	25,51	347,00	3330,00	135,79	85,42	457,00	12580,00	383,10	171,00	799,90
Share price 29.12.2011	17,30	126,79	790,00	25,51	346,00	3308,00	134,74	84,00	456,00	12556,00	382,00	170,47	778,10
Share price 28.12.2011	17,54	128,00	780,00	25,51	347,00	3283,00	134,34	82,56	451,70	12500,00	379,60	171,00	798,80
…	…	…	…	…	…	…	…	…	…	…	…	…	…
Share price 6.1.2009	9,17	445,50	846,00	259,60	429,00	3090,00	69,69	206,60	246,00	6255,00	453,30	147,50	637,20
Share price 5.1.2009	8,94	434,50	816,00	252,60	422,00	3101,00	70,15	205,30	236,30	6376,00	437,80	146,25	652,00
Share price 2.1.2009	9,19	408,50	804,00	262,50	421,00	3054,00	71,24	175,75	238,00	6426,00	425,50	146,00	645,00
Share price change 30.12.2011	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Share price change 29.12.2011	-0,03	-0,01	0,01	0,00	0,00	-0,01	-0,01	-0,02	0,00	0,00	0,00	0,00	-0,03
Share price change 28.12.2011	0,01	0,01	-0,01	0,00	0,00	-0,01	0,00	-0,02	-0,01	0,00	-0,01	0,00	0,03
…	…	…	…	…	…	…	…	…	…	…	…	…	…
Share price change 6.1.2009	0,02	0,07	0,03	0,01	0,03	0,04	0,00	-0,04	0,01	0,03	0,02	0,01	0,00
Share price change 5.1.2009	-0,03	-0,03	-0,04	-0,03	-0,02	0,00	0,01	-0,01	-0,04	0,02	-0,04	-0,01	0,02
Share price change 2.1.2009	0,03	-0,06	-0,01	0,04	0,00	-0,02	0,02	-0,17	0,01	0,01	-0,03	0,00	-0,01

Source: own calculations with use of **Patria Online, a.s. (2012)**