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ACCURACY IN RISK ESTIMATION BASED ON SIMPLE SMA AND EWMA MODELS: EVIDENCE FROM MACEDONIAN STOCK MARKET

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Abstract
Risk estimation or volatility estimation at financial markets, particularly stock exchange markets, is complex issue of great importance to theorists and practitioners. Models used to estimate volatility forecasts are translated into better pricing of stocks and better risk management. The aim of this research is to test applicability of simple models like Simple Moving Average (SMA) and Exponentially Weighted Moving Average (EWMA) to estimate risk. The performance of SMA and EWMA with rolling window of 100 using 0.94, 0.96, and 0.90 as smoothing constant were analyzed on investment activities of time series of 10 stocks comprising MBI-10. Binary Loss Function (BLF) is employed to measure accuracy of VaR calculations, because VaR models are useful only if they predict future risks accurately. Results show that risk managers can use SMA (100) and risk metric EWMA(100) smoothing constant of 0.96 model as a tool for estimating market risk at 95% confidence. At 99% confidence level both models failed to estimate risk accurately and permanently underestimate the risk.

Keywords: Value at Risk, Backtesting, Binary Loss Function, Risk Management, Capital Market.

Jel Classification: G17; C22; G32

INTRODUCTION

Basic relation in finance is a risk-return tradeoff. Risk means possibility that investor will receive a return on an investment that is different from the return he expected to make. Actual returns over holding period may be different from the expected returns and this difference is source of risk. The spread of the actual returns around the expected return is measured by the variance or standard deviation of the distribution; the greater

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the deviation of the actual returns from expected returns, the greater the risk (Damodaran, 2006).

Concerning risk measurement, there is a difference between a risk measure and a risk metric. Risk measure is result of the operation that assigns a value to a risk, while a risk metric, shows the attribute of risk that is being measured, like volatility, credit exposure, delta, beta and duration. The process of risk attributes calculation is a risk metrics.

Risk metrics enable to quantify exposure, to quantify uncertainty and to combine both which means to summarize risk with probability distribution (probabilistic risk metrics) by using standard deviation. Risk metrics can be applied for a specific category of risks and we distinguish market risk metrics, credit risk metrics etc. in accordance to metrics they assessed.

Crucial component of risk-return models is a issue of stock returns volatility, or uncertainty about future asset prices movements. Volatility is one of the manners that can provide a stylized representation of returns, usually defined as a conditional variance of returns that can change over time. Assets with a large volatility means that investor have more chances for higher returns but also for larger losses. Based on historical evidence there are many stylized stock return movements like volatility clustering, mean reverting, return with heavy tails (kurtosis) etc. There are three ways to calculate volatility: using high-frequency data, implied volatility of options data and by econometric modeling. This paper is focusing on the econometric modeling of volatility.

Better forecast of volatility can be transferred into better pricing of financial assets and better risk management. Stock market volatility has been intensively studied since 60’, but creating volatility-forecasting mathematical techniques started appearing the late 70’s, where mathematical modeling is used in detecting the dependencies between current values of the financial indicators and their future expected values. There are many different mathematical volatility forecasting models widely used in modern practice: historical (including moving averages), autoregressive, and conditional heteroscedastic models, implied volatility concept, a relatively new class of models – those based on artificial neural networks etc. As the volatility has positive and negative outcomes, risk management introduced new Value at Risk (VaR) measures that can capture only negative outcomes that shows possibility of loss. VaR has become the standard measure that financial analysts use to quantify market risk and it is used most often by commercial and investment banks to capture the potential loss in value of their traded portfolios from adverse market movements over a specified period. There are three key elements of VaR – a specified level of loss in value, a fixed time period over which risk is assessed and a confidence interval.

The main objective of this paper is to evaluate the accuracy of the most popular VaR methodology using simplest volatility forecasting models like SMA and EWMA and to address the research question: which conditional volatility model outperforms other model in terms of VaR? In accordance with this, the paper contributes to the debate into using VaR as a tool for risk management. The VaR can be specified for an individual asset to estimate risk and is calculated using SMA and EWMA with rolling window 100 using 0.94, 0.96, and 0.90 as decay factor, on the data of 10 stocks comprising official index MBI10 at the Macedonian Stock Market. For that purpose, VaR accuracy of these models was tested using Binary Loss Function test.

The remainder of the paper is organized as follow. After reviewing some of the literature on risk estimation in section 1, section 2 presents the methodology used. Section 3 provides description of data and analyses with the results regarding accuracy of the model used to estimate risk. The last section offers concluding remarks.

1. LITERATURE REVIEW

The works of Mandelbrot (1963) and Fama (1965) were the first few works that examined the statistical properties of stock returns; in the same strand Akgiray's (1989) work proceeds further which not only investigates the statistical properties but also presents evidence on the forecasting ability of ARCH and GARCH models vis-a-vis EWMA (exponentially weighted moving average) and the Historic simple average method. An excellent review of volatility forecasting can be found in Poon and Granger (2003). They reviewed the methodologies and empirical findings in more than 90 published and working papers that study forecasting performance of various volatility models. Pagan and Schwert (1990) report that GARCH and EGARCH models enhanced with terms suggested by nonparametric methods yields significantly increases in explanatory power.

In the same year Dimson and Marsh (1990) came up with rather interesting finding that simple models perform better than the exponential smoothing or regression based methods. Of course it has to be noted that their study does not include the popular ARCH family of models. In contrast to this Tse (1991), Tse and Tung (1992) find that EWMA models provide better forecasts than the GARCH models. These studies were conducted in different markets – the former was carried in UK stock market while the later examined in Japanese and Singapore markets respectively. Franses and Van Dijk (1996) examined the forecasting ability of the GARCH family of models against random walk model in five European stock markets and found that random walk model fares better even when the period of 1987 crash was included. West and Domgchui (1995) find evidence in favor of GARCH model over shorter intervals and in the longer horizon no model fare better.

VaR method attracts attention after it was published by J.P. Morgan/Reuters' Risk Metrics^{TM} Technical Document in 1996. It provides a set of techniques and data to measure market risks in portfolios of fixed and variable income instruments, foreign exchanges, commodities and their derivatives in over 30 countries (Guldimann et al. 1995).

Many authors went beyond and described alternative methods for calculating value-at-risk, so starting methods abounded with different names. More than one VaR model is currently used, but most practitioners grouped VaR models in three groups as follows the parametric method; the historical simulation method, and the structured Monte Carlo method (Holton 2014).

RiskMetrics has became the umbrella name for a series of VaR methodologies. In fact it groups two methodologies, an analytical approximation and a structured Monte Carlo simulation to calculate the VaR of nonlinear positions. Those two methods differ in a way how the value of portfolio changes as a result of market movements, where first method approximates changes in value, while second one revalues portfolios under various scenarios. Analytical VaR has limitations for portfolios whose P/L distributions may not be symmetrical and with normal distribution and it is overcome with Structured Monte-Carlo simulation where all instruments are marked to market under a large number of scenarios with volatility and correlation estimates.

Most of stock market volatility literature findings are based on the estimation of parametric ARCH or stochastic volatility models for the underlying returns, or on the analysis of implied volatilities from options or other derivatives prices. However, the validity of such volatility measures generally depends upon specific distributional assumptions, and in the case of implied volatilities, further assumptions concerning the market price of volatility risk (Andersen et al. 2001).

One of the econometric models that employed volatility is the equally weighted moving average model. It argues that all past squared returns that enter the moving average are equally weighted. However, such assumptions may lead to unrealistic estimates of volatility, and such limitation were overcome by the model of the exponentially weighted moving average (EWMA) proposed by J.P. Morgan's RiskMetrics^{TM} that assigns geometrically declining weights on past observations with the highest weight been attributed to the latest (i.e. more resent) observation. By assigning the highest weight to the latest observations and the least to the oldest the model is able to capture the dynamic features of volatility.

Already mentioned finance literature and practice widely explore risk-return models in developed markets and have clear conclusion about advantages and disadvantages of different models. However, there are fewer findings concerning stock exchanges with lower maturity of the market, like Central and Eastern Europe stock exchanges.

Volatility of stock returns is widely explored topic in scientific papers but mainly in context of the developed stock markets in industrial countries (Green, Maggioni, and Murinde 2000). Most authors use ARCH models introduced by Engle (Engle 1982) and its extensions made with Bollerslev (1986).

On the other side, there are limited numbers of studies for emerging markets (Shiller 1990; Flores 1997). First authors that investigate volatility of Eastern Europe markets were Bolt and Milobedzki (1994) that analyze the return on shares quoted on the Warsaw Stock Exchange in the period 1991–1993 and confirmed high volatility. Their findings were confirmed by Flores and Szafarz (1997) and Nivet (1997). Dockery and Vergari (1997) confirmed the random walk hypothesis using variance test ratio on weekly returns at the Budapest stock exchange. This was confirmed by other authors with conclusion that emerging stock markets are characterized by high volatility (Aggarwal et al. 1999).

Volatility of stock markets of other countries from Central and Eastern Europe and especially for the countries that used to be part of former Yugoslavia were rarely considered in scientific journals, so it is difficult to derive final and comprehensive conclusions. Angelovska (2013) is testing VaR models on seven stock exchange indices from developed and emerging market and argue that RiskMetrics EWMA can be used in estimating VAR in terms of accuracy for measuring market risk not just in developed countries, but in developing countries. Kovacic (2007) by using GARCH-type models derived conclusions that MSE returns series are characterized with volatility clustering. Bogdan, Baresa and Ivanovic (Bogdan et al. 2015) derived conclusion that weighted historical models give more representative results of the risk assessment compared with historical VaR method. Several authors (Ivanovski et al. 2015) argue that the MSE values for volatility of the volatility sequence are very similar when calculated using RWMA and EWMA methods. Murinde and Poshakwale (2001) apply ARIMA, the BDSL procedure and symmetric as well as asymmetric GARCH models to test for daily return volatility at Croatia, Czech Republic, Hungary, Poland, Russia and Slovakia Stock-Exchanges and conclude that in all the six markets, volatility exhibits significant conditional heteroskedasticity and non–linearity.

Research findings for volatility of emerging markets of Central and Eastern Europe are usually based on different risk-return models that indicate a need for further investigations and research papers for the nature of volatility.

2. METHODOLOGY

Risk can be defined as the volatility of unexpected outcomes, and refers to possible losses in financial markets. Volatility is associated with the sample standard deviation of returns over some period of time and is calculated using following formula:

$$\sigma_t = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \mu)^2} \quad (1)$$

r_t is the return of an asset over period t

μ is an average return over T periods.

Volatility is a quantified measure of risk, but volatility measures a spread of outcomes desirable positive and negative or the uncertainty of a negative outcome associated with risk. To measure maximum loss at a given confidence level over a target horizon new measure was introduced as Value-at-Risk.

VaR measures maximum loss at a given confidence level. VaR calculation requires first to define three parameters: VaR forecast horizon, confidence level (probability that the realized change in portfolio will be less than the VaR prediction) and the base currency. Second step in VaR calculation is mapping forecasted and marked-to market cash flows to Risk Metrics vertices. Third step is making decision how to compute VaR. The mathematical definition of VaR is:

$$VaR = -\kappa(\alpha) * P * \sigma_P \quad (2)$$

σ_p is the portfolio's standard deviation
P is the value of the portfolio
κ(α) is the desirable level of confidence (l-α)% quantile of the standard normal distribution.

The aim of this research is to evaluate the accuracy of the most popular VaR methodology using simplest volatility forecasting models like SMA and EWMA.

The Moving Average is a tool that helps to identify current price trends and the potential for a change in determined trend. It is an average of a set of variables such as stock prices over time. A Simple Moving Average (SMA) model is a modified version of the historical average model, and probably the most widely used volatility model in Value at Risk research papers. This model logic lies in volatility defined as the equally weighted average of realized volatilities in the past 'n' days. In fact it is an arithmetic moving averages calculated by adding the closing price of the security for a number of time periods and then dividing this total by the number of time periods:

$$\sigma_t^2 = \frac{1}{n}\sum_{i=1}^{n}\sigma_{t-i}^2 \tag{3}$$

The n-day Simple Moving Average takes the sum of the last n days prices. A simple moving averages smoothes out volatility and enables to identify the price trend of a security, if it points up it indicates that security price is increasing and vice versa when pointing down it means that the security price is decreasing.

The Exponential Weighted Moving Averages (EWMA) model computes a weighted average of the sequence by applying weights that decrease geometrically with the age of the observations. This model calculates a value for a given time on the basis of the previous day's value. The model is using the latest observations with the highest weights for volatility estimations. The EWMA is the simplest model for σ_{t+1} and follows equation:

$$\sigma_n = \lambda * \sigma_{n-1}^2 + (1-\lambda) * r_{n-1}^2 \tag{4}$$

σ_n^2 is dispersion estimate for the day n calculated at the end of day (n-1)
σ_{n-1}^2 is dispersion estimated for the day (n-1)
r_{n-1} is asset's return for the day (n-1). Return for the day n is natural logarithm of the ratio of stock's price from the day n to previous day n-1
λ is decay factor. The EWMA model depends on the parameter $\lambda(0(\lambda)1)$ referred to as the decay factor.

The EWMA model has a memory and it gives her advantage compared with SMA. The EWMA remembers a fraction of its past by a factor, λ and it makes her good representative for the history of the price movement.

It is very difficult to predefine the right decay factor, beside RiskMetrics determined 0.94 as the decay factor for one-day time horizons, and in this study 0.90 and 0.96 as decay factor or smoothing constant are used to test which is better to estimate VaR at Macedonian Stock Market. In this study calculations are based on a 100-day rolling window, that is, for every day in the sample period a mean is estimated based on returns over the last 100 days.

To test accuracy of the models, Binary Loss Function (BLF) is used, based on whether the actual loss is larger or smaller than the VaR estimate. BLF is simply concerned with the number of failures rather than the magnitude of the exception and if the actual loss is larger than the VaR then it is termed as an "exception" (or failure) and is equal to 1, with all others being 0. The sum of the number of failures across all dates is divided by the sample size. The obtained BLF is the rate of failure that should be close to the chosen confidence level to show accuracy of the model. In this study, the accuracy is defined as the rate of failure (or exception) associated with how close each specific model came to the pre-set level of significance.

3. DATA

The data used in this study consist of the daily closing prices of 10 listed ordinary shares, chosen by the Stock Exchange Index Commission, according to the criteria from the Methodology for calculation of the Macedonian Stock Exchange Index - MBI10 with the last revision: Alkaloid AD Skopje, Stopanska banka AD Skopje, Granit AD Skopje, Komercijalna Banka AD Skopje, Makpetrol AD Skopje, Stopanska Banka AD Bitola, Makedonijaturist AD Skopje, Ohridska banka AD Ohrid, NLB Banka AD Skopje and Makedonski Telekom AD Skopje. Index MBI10 was introduced since January 4th 2005 as a price index weighted with the market capitalization. Composition of the index is done from all shares that were listed on the Official market of the Macedonian Stock Exchange. Table 1 shows composition of MBI10 with the last revision with number of total shares, their symbols and value of Free Flow (FF) market capitalization on the date of revision in Euro. Alkaloid AD Skopje has highest FF market capitalization followed by Komercijalna Banka AD Skopje.

Table 1. Composition of MBI 10 (last revision 15.12.2017)

Issuer	Symbol	Total shares	FF Market Capitalization on the date of revision in EUR
Alkaloid AD Skopje	ALK	1.431.353	156.205.214
Stopanksa banka AD Skopje	STB	17.460.180	13.847.768
Granit Skopje	GRNT	3.071.377	37.742.367
Komercijalna banka Skopje	KMB	2.279.067	90.050.940
Makpetrol Skopje	MPT	112.382	38.056.063
Stopanska banka Bitola	SBT	390.977	9.926.481
Makedonski Telekom AD Skopje	TEL	95.838.780	18.217.316
Makedonijaturist AD Skopje	MTUR	452.247	17.954.206
NLB banka AD Skopje	TNB	854.061	23.704.428
Ohridska banka AD Skopje	OHB	438.586	10.193.769

Source: Macedonian Stock Exchange

The sample covers a period from January 4th 2005 when MBI 10 was introduced till April 2nd 2018. The high frequency data incorporated here include information on short-run market interactions that may be absent in lower frequency data. The data were obtained from Macedonian Stock Exchange database. The daily return is calculated as the change in the logarithm of the closing price on successive days. The number of trading days (observations) is different for all the shares due to thin stock market liquidity, or there is no trading volume for all shares every day. Additionally index MBI10 is used as well for calculation and for comparison. Table 2 reports basic descriptive statistics for the time series of stock market returns that are of prime interest to investors' portfolios. All stock return series show leptokurtosis and there is evidence of negative (long left tail) and positive (long right tail) skewness.

Skewness is a particular feature of returns in Balkan emerging markets. Significant kurtosis (much higher than 3) and skewness indicate rejection of normality in stock return distributions. Highest mean return has Ohridska Banka AD Skopje, followed by Makedonija Turist AD Skopje, Granit AD Skopje, Alkaloid AD Skopje, Makpetrol AD Skopje, Telekom AD Skopje. Tutunska Banka AD Skopje, Komercijlna Banka Skope and Stopanska Banka AD Bitola have negative mean return. They are followed by high standard deviation. The lowest standard deviation has Alkaloid AD Skopje and the most trading days or number of observation. MBI 10 has mean return 0.03 with standard deviation of 1.3, negative skewness and high kurtosis.

Table 2. Descriptive statistics of the MBI10 and stocks composition in the period January 4th to April 2nd 2018

	#Obs.	Mean	St.dev.	Skewness	Kurtosis
ALK	3073	0,041	1,799	0,006	10,76
KMB	3017	-0,003	3,361	-2,866	12,92
STB	1685	0,021	4,445	0,019	23,55
GRNT	2769	0,081	2,627	0,471	8,00
MPT	2663	0,031	2,641	0,087	6,78
SBT	1993	-0,008	2,771	-0,124	5,56
TEL	1685	0,020	4,446	-1,168	41,65
MTUR	1464	0,133	2,249	0,506	7,98
TNB	2382	-0,013	2,537	0,110	41,65
OHB	1172	0,157	3,717	-0,167	9,80
MBI10	3233	0,032	1,267	-0,130	13,30

Source: Macedonian Stock Exchange

4. EMPIRICAL RESULTS

Mean and standard deviation of each stock comprising MBI 10 and index MBI 10 were calculated with simple models SMA and EWMA. Rolling window of 100 observations was used for both models and different smoothing constant λ of 0,90; 0,96 and 0.94 (proposed by Risk Metrics) for calculating EWMA. VaR models are calculated for a one-day holding period at 95% and 99% coverage of the market risk. The accuracy of calculated volatility of both models with roling window of 100 and diffrenet smoothing constant for EWMA model calculations are tested with BLF test. The BLF test provides a point estimate of the probability of failure. In other words, the accuracy of the VaR model requires that the BLF, on average, is equal to one minus the prescribed confidence level of the VaR model.

Table 3. Tests Based on Value-at-Risk Approach BLF- 5%

	SMA	EWMA 0,96	EWMA 0,90	EWMA 0,94
ALK	5,2%	5,6%	6,8%	5,8%
KMB	5,4%	5,7%	7,5%	6,6%
STB	4,5%	4,7%	6,1%	5,6%
GRNT	5,3%	5,6%	6,8%	6,1%
MPT	4,2%	5,2%	7,0%	5,8%
SBT	5,6%	6,0%	7,5%	6,7%
TEL	4,3%	5,4%	7,0%	5,9%
MTUR	4,4%	6,0%	6,9%	6,2%
TNB	4,2%	4,9%	6,8%	5,7%
OHB	4,9%	5,7%	6,5%	6,3%
MBI10	4,6%	4,8%	6,1%	5,3%

Table 3. (Authors' Calculations) shows the rate of failure of the models employed for calculating VaR, at 95% confidence level. At 95% confidence level SMA (100) model and EWMA (100), with smoothing constant λ of 0,96 work good to estimate risk for most of the shares of MBI10. Risk estimation for ALK, KMB, GRNT. OHB and SBT

is better to be done with simple SMA model. Volatility of STB, MPT, TEL, TNB and MTUR is better to be estimated with EWMA (100) smoothing constant 0,96. Risk metrics EWMA model 0.94 (proposed by Risk Metrics) is best to estimate risk for the index MBI10.

Table 4. Tests Based on Value-at-Risk Approach BLF- 1%

	SMA	EWMA 0,96	EWMA 0,90	EWMA 0,94
ALK	2,5%	2,6%	3,5%	3,4%
KMB	1,9%	2,3%	3,3%	2,7%
STB	1,8%	1,9%	2,3%	2,0%
GRNT	1,7%	2,1%	3,0%	2,4%
MPT	1,7%	2,3%	3,0%	2,5%
SBT	2,3%	2,5%	3,6%	2,7%
TEL	2,0%	2,4%	3,2%	2,5%
MTUR	2,2%	2,6%	3,6%	2,9%
TNB	2,0%	2,0%	3,0%	2,2%
OHB	1,9%	3,0%	3,9%	3,1%
MBI10	1,7%	1,7%	2,3%	1,8%

Table 4. (Authors' Calculations) shows the rate of failure of the models employed for calculating VaR, at 99% confidence levels. The backtesting results using BLF method shows that at high quantiles (99) both models failed. The risk is underestimated with both models. Risk estimation for the 10 shares used in this study, better works with SMA(100) model than Risk metrics EWMA. Using EWMA (100) at 99% confidence level works better with λ of 0,96 than with 0.94 and 0.90 even though risk is underestimated. Estimation volatility for MBI10 at 99% confidence levels can be done the same with both models: SMA (100) and EWMA (100) with λ of 0,96 and 0.94.

CONCLUSION

Simple SMA and EWMA models are used to calculate the volatility of the daily stock returns of the 10 shares comprising index MBI10 to find out if they are working well for stock risk estimation and which model works better. Rolling window that is used is 100 observation for both models and for EWMA model, different smoothing constant λ is used: 0.90, 0.94 and 0.96. Risk Metrics model is based on the unrealistic assumption of normally distributed returns, and completely ignores the presence of fat tails in the probability distribution, a most important feature of financial data and even though it is expected that will seriously underestimate risk it was found that works satisfactorily well. Due to the simplicity, this model is widely used and the goal of this study was to check if it works for risk estimation on the Macedonian Stock Market.

Systematic backtesting was a part of regular VaR reporting in order to constantly monitor the performance of the model. Risk managers at MSE can use SMA (100) model and EWMA (100), with smoothing constant λ of 0.96 to estimate risk for most of the shares of MBI-10 at 95% confidence level. Risk estimation for ALK, KMB, GRNT, OHB and SBT is better to be done with simple SMA model. Volatility of STB, MPT, TEL, TNB and MTUR is better to be estimated with EWMA (100) smoothing constant of 0.96. Risk metrics EWMA model 0.94 (proposed by Risk Metrics) is best to estimate risk for the index MBI10. The backtesting results using BLF method shows that at high quintiles (99) both models failed. The risk is underestimated with both models. Using EWMA (100) at 99% confidence level works better with λ of 0.96 than with 0.94 and 0.90 even though risk is underestimated. Estimation volatility for MBI-10 at 99% confidence level can be done the same with both models: SMA (100) and EWMA (100) with λ of 0.96 and 0.94.

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