Reward-to-Variability Ratio as a Key Performance Indicator in Financial Manager Efficiency Assessment

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Abstract. In this paper computational techniques to process financial data and to assess management efficiency are proposed. Personnel evaluation process is formalized on the basis of the proposed key performance indicators based on portfolio efficiency criteria. Personnel efficiency is assessed via the excessive portfolio return over average market performance indicators per unit of risk. Alternative measures to evaluate risk are formulated. The proposed downside risk measures are implemented into portfolio performance evaluation criteria. Comparative analysis of the introduced portfolio performance evaluation criteria is held. Case study via the Trading Organiser 'Moscow Exchange' is performed. The experimental results prove that the introduced portfolio performance evaluation criteria yield better results than the coefficients which do not take into account downside risk measures. It is concluded that the proposed modified 'reward-to-variability' ratio can be incorporated into the system of key performance indicators for assessing financial management efficiency. #CSOC1120.

Keywords: Key performance indicator · Portfolio performance · Sharpe coefficient · Reward-to-variability ratio · Reward-to-volatility ratio · Value at risk

1 Introduction

Quantitative indicators have become widely used in personnel assessment recently due to their recognition as more objective criteria and their convenience in planning personnel management and personnel evaluation processes. For this, various scores, labor contribution factors or labor participation rates, ratings, scales, key performance indicators, and a balanced scorecard are used. One of the conditions to apply such criteria is information processing, e.g. processing personnel statistics, labor indicators, financial and economic indicators of the organization and of the market as a whole. Thus, there is a strong need for techniques to formalize data and evaluation process.

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In assessing the results of personnel in the financial sector, one of the key issues remains the evaluation of investment portfolio efficiency. One of the most discussed problems in this respect is the choice of a criterion that most fully and objectively reflects the contribution of the investment analyst or financial manager to the excessive portfolio return over average market performance indicators.

In the present state of the art there are different criteria developed to evaluate financial manager performance, as is demonstrated by many publications on this subject [1, 2]. From the point of view of portfolio diversification the Sharpe coefficient (reward-to-variability ratio) and the Treynor coefficient (reward-to-volatility ratio) most fully reveal the excessive return of risk premium per unit of risk measure. The difference between these approaches is the way to measure risk: the Sharpe coefficient is based on the variance of the portfolio return while the Treynor coefficient takes into account 'beta' of the portfolio, that is its correlation with the market portfolio average return [1, 3].

Despite various modifications of these coefficients [1, 2], the researchers note such their shortcomings as the instability of beta in time, the assumption of the normal or symmetric distribution of financial assets return, which is not fully proved in practice [5, 6]. In particular, in emerging markets economy (to which researchers include, among others, the financial market of Russia and Eastern Europe as well), the financial assets return is closer to the 'downside' distribution, that is, the actual return is shifted to the left, below the average (expected) return, which implies increased investment risk, and therefore, requires taking these deviations into account when constructing Sharpe and Treynor coefficients to assess financial manager performance.

The aim of this paper is to propose new portfolio performance criteria based on the Sharpe coefficient to assess financial manager efficiency. We modify the Sharpe coefficient using the new introduced $(\overline{R} - VaR)$- and $(\overline{R} - R_{low})$-risk measures. The new measures are based on VaR- and $Rlow$-values, which refer to the downside risk measures.

The paper is organized as follows. The techniques of diversification, portfolio performance criteria and modifications of the Sharpe coefficient, based on the new introduced risk measures, are discussed in the second section. An illustrative example is presented in the third section, it is performed via the open trade system of Moscow Exchange and it includes case study of portfolio diversification, portfolio performance evaluation and testing of the selected portfolios. The results of model verification are discussed in the forth section. The main findings of the research are summarized in the conclusion.

2 Methods

2.1 Portfolio Diversification Techniques

First we introduce some concepts to characterize an individual asset.

The monthly moving return at time t of the asset i, $i = \overline{1, n}$ is defined as:

$$R_{it} = \frac{P_{it}}{P_{i(t+1-m)}}, \quad t = \overline{m, N} \tag{1}$$

where $P_{it}, P_{i(t+1-m)}$ are the amounts of money received at the end and invested at the beginning of a period of one 21-day month, *m* = *22*, and *N* is the number of observed values of prices for a period of one 252-day-year, *N* = *252*.

The mean value of return on the asset *i* is:

$$\overline{R}_i = \frac{1}{N}\sum_{t=m}^{N} R_{it} \tag{2}$$

The risk of the asset *i* is characterized by the variance of the return:

$$\sigma_i^2 = \frac{1}{N-1}\sum_{t=m}^{N} (R_{it} - \overline{R}_i)^2 \tag{3}$$

The covariance summarizes the mutual dependence of two assets *i* and *j*:

$$Cov_{ij} = \frac{1}{N-1}\sum_{t=m}^{N} (R_{it} - \overline{R}_i)(R_{jt} - \overline{R}_{jt}) \tag{4}$$

The Market model assumes that an individual asset is correlated with the market portfolio, which can be evaluated by the market index (for example, *S&P*, *DJIA, IMOEX*). Thus, the Market model implies a special structural property for the return of the asset. The expected return on the asset *i*, $i = \overline{1,n}$, is assumed in the form [1]:

$$R_i = \alpha_{iI} + \beta_{iI} \cdot R_I + \varepsilon_{iI}, \tag{5}$$

where α_{iI} is the shift coefficient, β_{iI} is the slope coefficient, ε_{iI} is a random variable, R_I is the return on the market index. One has:

$$\alpha_{iI} = \overline{R}_i - \beta_{iI} \cdot \overline{R}_I, \tag{6}$$

where $\overline{R}_i$ and $\overline{R}_I$ are the mean returns on the asset and on the index, respectively, obtained using (2).

The coefficient β_{iI} represents the sensitivity of asset *i* to market movement. 'Beta' shows how much the asset performance moves when the market moves:

$$\beta_{iI} = \frac{Cov_{iI}}{\sigma_I^2}, \tag{7}$$

where Cov_{iI} is the covariance between the return on the asset and the return on the index; σ_I^2 is the variance of the return on the index.

For the further analysis we consider the Index I_t of the Trading Organiser ‘Moscow Exchange’ – MOEX Russia Index (*IMOEX*) [8], that is defined as follows:

$$I_t = I_0 \cdot \frac{MC_t}{MC_0}, \tag{8}$$

where MC_t and MC_0 are the total market capitalization of Index component stocks on the current date t and on the initial date *0*, and I_0 is the Index value on the initial date. Thus,

$$MC_t = \sum_{i=1}^{k} P_{ti} \cdot Q_{ti},\ t = \overline{1, N}, \tag{9}$$

where Q_{ti} is the number of stocks i existing on the current date t, P_{ti} is the price of unit stock i on the time t, k is the total number of component stocks used in the Index calculation.

The risk of the asset i is measured by the variance:

$$\sigma_i^2 = \beta_{iI}^2 \cdot \sigma_I^2 + \sigma_{\varepsilon i}^2, \tag{10}$$

where $\sigma_{\varepsilon i}^2$ is the variance of the random variable ε_{iI}.

The mean return of a portfolio of n assets is obtained as:

$$R_p = \sum_{i=1}^{n} w_i \cdot \overline{R}_i, \tag{11}$$

where w_i is the weight of the asset i in the portfolio.

The variance of a portfolio return is defined as [7]:

$$\sigma_p^2 = \sum_{ij} w_i \cdot w_j \cdot Cov_{ij} \tag{12}$$

Assuming that the portfolio consists of n assets and letting the weighting coefficients w_i range over all possible combinations such that $\sum_{i=1}^{n} w_i = 1$, we can plot the mean - standard deviation diagram of the feasible set of portfolios and obtain the efficient frontier, as shown on Fig. 1.

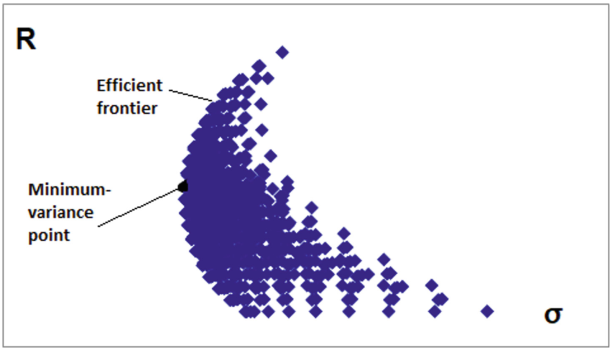

Fig. 1. Feasible set of portfolios

The left part of the boundary is the minimum-variance set and the upper portion of this set forms the efficient frontier of the feasible set.

The points of the efficient frontier are obtained by solving the optimization problem: to minimize the variance of the portfolio under fixed value R of the mean return. That is [7]:

$$J = \sum_{ij} w_i \cdot w_j \cdot Cov_{ij} \to \min \tag{13}$$

subject to

$$\sum_{i} w_i \cdot \overline{R_i} = R \tag{14}$$

$$\sum_{i} w_i = 1$$

$$w_i \geq 0,\ i = \overline{1, n}$$

The solutions of the problems yield the optimal weight coefficients w_i^* for the assets in the portfolio.

2.2 Reward-to-Volatility and Reward-to-Variability Ratio

As a result of solving the optimization problem, the investor obtains a set of portfolios on the efficient frontier. The question is to select a portfolio from the efficient set.

One strand of the literature is based on constructing indifference curves [7]. We consider this approach rather subjective, since it assumes that the investor is able to compare various combinations of portfolio risk and return and to determine which of the combinations are equivalent for him.

Another strand of literature aims at finding the tangent portfolio. Such an approach is implemented in the Tobin model, the Elton – Padberg – Gruber algorithm [3]. The commonly used portfolio performance indicators are the Sharpe and Treynor coefficients, which measure the risk premium per unit of risk. Thus, as a criterion for choosing the optimal portfolio from the efficient set, it is proposed to maximize the risk premium per unit of risk.

The Sharpe coefficient, known as the ‘reward-to-variability ratio’, is defined to be [1]:

$$RVAR_p = \frac{R_p - R_f}{\sigma_p}, \tag{15}$$

where R_p is the mean-return of the portfolio p, R_f is the risk-free asset return, and σ_p is the standard deviation of the portfolio p.

The Treynor coefficient (the ‘reward-to-volatility ratio’) is assumed to be [1]:

$$RVOL_p = \frac{R_p - R_f}{\beta_p}, \tag{16}$$

where β_p is the ‘beta’-coefficient of the portfolio p, that is defined in the Market Model [1].

The Sharpe coefficient (15) and Treynor coefficient (16) can be equally used for assets evaluation:

$$RVAR_i = \frac{\overline{R}_i - R_f}{\sigma_i} \tag{17}$$

$$RVOL_i = \frac{\overline{R}_i - R_f}{\beta_i}, \tag{18}$$

where $\bar{R}_i$ is the mean return of the asset i, $i = \overline{1, n}$, σ_i is the standard deviation and β_i is the coefficient of sensitivity of the asset i to market movement.

The choice of a security i^* to be added into a portfolio can be based on the maximization of the Sharpe coefficient (17) or the Treynor coefficient (18), i.e. $i^* = \arg\max_i RVAR_i$ or $i^* = \arg\max_i RVOL_i$, $i = \overline{1, n}$. It means a preference is given to the asset having the largest market prime per risk-unit, measured by the standard deviation (the Sharpe coefficient) or by the ‘beta’-value (the Treynor coefficient).

The choice of the coefficient depends on the set of the financial assets in the investor’s portfolio. The risk for an investor, possessing other assets that are not included in the portfolio, should be measured by the ‘beta’-coefficient since this coefficient evaluates risk relatively to the market. When all instruments are included in the portfolio under consideration, the standard deviation can be seen as a suitable risk-measure, and the Sharpe coefficient can be used as asset evaluation criterion.

2.3 Modifications of the ‘Reward-to-Variability’ Ratio

Reward-to-volatility and reward-to-variability ratio assume the normal or symmetric distribution of financial assets return. However in emerging markets economy the financial assets return is closer to the ‘downside’ distribution, that is, the actual return is shifted to the left, below the average (expected) return, which implies increased investment risk, and therefore, requires taking these deviations into account when constructing performance evaluation criteria.

We introduce a new parameter, termed 'low-mean' return of the asset i, defined as:

$$\overline{R}_{ilow} = \sum_{t \in Z^-} p_{it} \cdot R_{it},\ R_{it} < \overline{R}_i, \tag{19}$$

where Z^- is the set of indices t such that $R_{it} < \overline{R}_i$, and p_{it} is the probability of the return R_{it}.

$\overline{R}_{ilow}$ is the mean-return of a left ('bad') part of the return distribution of the asset i, i.e. the mean-value for the returns, which are less than the mean return of the asset $\overline{R}_i$.

We define a new risk-measure, namely the difference between the asset mean return and the 'low-mean' return $(\overline{R}_i - \overline{R}_{ilow})$.

The value-at-risk (VaR) is a measure widely used in financial analysis. For a known asset return distribution, VaR defines the return that can be achieved with some probability level [2]:

$$VaR_i = R_{iVaR} : [P\{R_{it} > R_{iVaR}\} = 1 - \alpha], \tag{20}$$

where α is the confidence level, which is usually set equal to 0.01, 0.05, or 0.1.

In the present paper we use method of historical modeling to calculate VaR considering inconsistency of the parametric VaR-models with the Russian stock market. This method is based on empirical distribution for a given period. VaR represents a quantile of an empirically estimated return distribution.

We propose another new risk measure, namely the difference between the asset mean return and the VaR-value for α-confidence level $(\overline{R}_i - VaR_i)$. The choice of the confidence level depends on the investor's attitude to risk. Risk preference allows setting high confidence-level, that increases VaR-value and decreases investor subjective evaluation of risk, measured by $(\overline{R}_i - VaR_i)$-value. And on the contrary, risk aversion implies low confidence-level.

On the base of the risk-measures, we propose the following modifications of the Sharpe coefficient for the asset i:

$$S_{ilow} = \frac{\overline{R}_i - R_f}{\overline{R}_i - \overline{R}_{ilow}} \tag{21}$$

$$S_{iVaR} = \frac{\overline{R}_i - R_f}{\overline{R}_i - VaR_i} \tag{22}$$

The coefficient (21) describes the amount of excessive return (market prime) referred to unit of risk, measured as a deviation of asset mean return from its 'low'-mean return. This coefficient may be recommended to evaluate especially the assets characterized by asymmetric distribution.

The coefficient (22) describes the amount of excessive return per unit of risk, measured as a deviation of asset mean return from its VaR-value. VaR-value can be estimated for different α-confidence levels, which are set regarding the investor's risk preferences.

The proposed modifications of the Sharpe coefficient are based on introduced 'downside' risk measures: ($\overline{R}_i - \overline{R}_{ilow}$)- and ($\overline{R}_i - VaR_i$)-measures.

We propose the following modifications of the Sharpe coefficient for the portfolio:

$$S_{plow} = \frac{\overline{R}_p - R_f}{\overline{R}_p - \overline{R}_{plow}} \tag{23}$$

$$S_{pVaR} = \frac{\overline{R}_p - R_f}{\overline{R}_p - VaR_p} \tag{24}$$

The coefficient (23) describes the amount of excessive return (market prime) referred to unit of risk, measured as a deviation of portfolio mean return from its 'low'-mean return.

The coefficient (24) describes the amount of excessive return per unit of risk, measured as a deviation of portfolio mean return from its VaR-value. VaR-value can be estimated for different α-confidence levels, which are set regarding the investor's risk preferences.

The modified coefficients may be recommended to evaluate especially the portfolio characterized by asymmetric distribution, which is typical to emerging markets economy. It is noted, that the financial assets return in developing countries is closer to the 'downside' distribution, that is, the actual return is shifted to the left, below the average (expected) return, which implies increased investment risk, and therefore, requires taking these deviations into account when assessing portfolio efficiency.

3 Results

3.1 Portfolio Optimization

The experimental case study has been performed via open trade system operated by the Trading Organiser 'Moscow Exchange' – Equity and Bond Market (MICEX SE), which lists leading Russian securities that are of great interest to both domestic and foreign portfolio investors [8].

According to a principle of diversification, we consider an investor who distributes the invested amounts among different branches of economy, represented by the following companies: Public Joint Stock Company Gazprom (ordinary share *GAZP*), Public Joint Stock Company "Mining and Metallurgical Company "NORILSK NICKEL" (ordinary share *GMKN*), Public Joint Stock Company "Aeroflot-Russian Airlines" (ordinary share *AFLT*), Public Limited Liability Company Yandex N.V., shares of a foreign issuer (ordinary share *YNDX*), Rosneft Oil Company, ordinary share (ordinary share *ROSN*), Public Joint Stock Company "Magnit", (ordinary share *MGNT*), Mobile TeleSystems Public Joint Stock Company, ordinary share (ordinary share *MTSS*), Sberbank of Russia, ordinary share (ordinary share *SBER*).

We have studied statistic data on selected securities for a one-year period, namely December 2018 – December 2019. We suppose the amounts are invested for a one-month period considering a professional prudent investor who performs market monitoring regularly. Monthly-moving returns have been obtained using (1).

The securities mean returns, standard deviations and 'beta'-coefficients have been calculated using (2), (3), (7). The significance of the 'beta'-coefficients is confirmed by the high values of the coefficient of determination R^2. The results are shown in Table 1.

Table 1. Securities parameters for the period January 2019 – December 2019

Asset	Asset parameters			
	R_i	σ_i	β_{iI}	R^2
GMKN	1,030672	0,049349	1,011474	0,997799
AFLT	1,002309	0,050455	0,983576	0,997429
GAZP	1,041405	0,096502	1,023033	0,993589
MGNT	0,995392	0,063206	0,977365	0,997124
MTSS	1,021866	0,049885	1,003441	0,998921
ROSN	1,005757	0,040527	0,987094	0,998606
YNDX	1,029459	0,083607	1,010474	0,993925
SBER	1,021043	0,058033	1,002838	0,998487

The high values of the R^2-coefficient indicate that the funds' fluctuations are explained by performance fluctuations of the index [5]. Among the selected assets the *GAZP*-asset may be considered to be affected by factors other than the market to the highest degree. The return and the variance of the *IMOEX* Index are as follows: R_I = 1,018437; σ_I^2 = 0,00119. These values have been obtained using (1), (2) and (3).

We have determined the values of the $RVAR_i$-, $RVOL_i$-, and the introduced S_{ilow}- and S_{iVaR}-coefficients, using (17), (18), (21) and (22). The coefficient S_{iVaR} has been calculated for the confidence levels $\alpha = 0.05$ and $\alpha = 0.1$ to assess different risk preferences. The annual expected risk-free rate of return in (17), (18), (21) and (22) is supposed to be 7% as it is estimated for governmental bonds in Russia in 2019 [8]. Thus, annual risk-free return R_f is set equal to 1.07, that is 1.0057 for a one-month period as geometric mean in the considered example. The results are shown in Table 2.

Table 2. Assets performance evaluation criteria

Asset	Asset performance evaluation criteria				
	$RVAR_i$	$RVOL_i$	S_{ilow}	S_{iVaR}, $\alpha = 0.05$	S_{iVaR}, $\alpha = 0.1$
GMKN	0,506954	0,024734	0,750596	0,33616	0,448125
AFLT	−0,06629	−0,0034	−0,12712	−0,04839	−0,05287
GAZP	0,370464	0,034946	0,649321	0,332226	0,385877
MGNT	−0,16236	−0,0105	−0,2247	−0,11704	−0,14175
MTSS	0,324978	0,016156	0,440203	0,225581	0,288132
ROSN	0,002546	0,000105	0,003454	0,001874	0,002143
YNDX	0,284718	0,023558	0,41742	0,199424	0,259973
SBER	0,265184	0,015346	0,346886	0,181994	0,217683

The assets have been ranged according to the $RVAR_i$-, $RVOL_i$-, S_{ilow}- and S_{iVaR}-coefficients, as shown in Table 3.

Table 3. Ranking of the assets according to performance evaluation criteria

Asset performance evaluation criteria				
$RVAR_i$	$RVOL_i$	S_{ilow}	S_{iVaR}, $\alpha = 0.05$	S_{iVaR}, $\alpha = 0.1$
GMKN	GAZP	GMKN	GMKN	GMKN
GAZP	GMKN	GAZP	GAZP	GAZP
MTSS	YNDX	MTSS	MTSS	MTSS
YNDX	MTSS	YNDX	YNDX	YNDX
SBER	SBER	SBER	SBER	SBER
ROSN	ROSN	ROSN	ROSN	ROSN
AFLT	AFLT	AFLT	AFLT	AFLT
MGNT	MGNT	MGNT	MGNT	MGNT

Note, that the applied assets criteria have yielded almost the same results indicating the most efficient assets.

We have composed the portfolio of 6 upper assets, selected from the Table 2 and having the highest $RVAR_i$-, $RVOL_i$- S_{ilow}-, and S_{iVaR}-coefficient values, namely *GMKN*-, *GAZP*-, *MTSS*-, *ROSN*-, *YNDX*-, and *SBER*-assets.

Covariance matrix of the selected assets has been constructed using (4). The results are shown in Table 4.

Table 4. Covariance matrix for the selected assets

Asset	Cov_{ij}					
	GMKN	GAZP	MTSS	ROSN	YNDX	SBER
GMKN	0,002425644	−0,0008194	0,00125529	0,0008496	0,00124137	0,0001964
GAZP	−0,00081943	0,00927567	0,00093926	0,0004933	−0,0005654	0,0013511
MTSS	0,00125529	0,00093926	0,00247863	0,0006858	0,00184348	0,001375
ROSN	0,00084958	0,00049325	0,00068577	0,0016359	0,00067571	0,0010505
YNDX	0,00124137	−0,0005654	0,00184348	0,0006757	0,00696243	0,0010723
SBER	0,000196394	0,00135105	0,00137501	0,0010505	0,00107226	0,0033544

We have solved the variance-minimizing problem to find the efficient frontier of a feasible set. Remind that the efficient frontier is the upper portion of the minimum-variance set that lays upper than a minimum-variance point. The points on the efficient frontiers have been determined by solving the optimization problem (13), (14): minimize the variance of the portfolio under the constraint of a fixed mean return σ. The fixed values R in (14) have been chosen using a 0.1% step.

The obtained results are shown in Fig. 2.

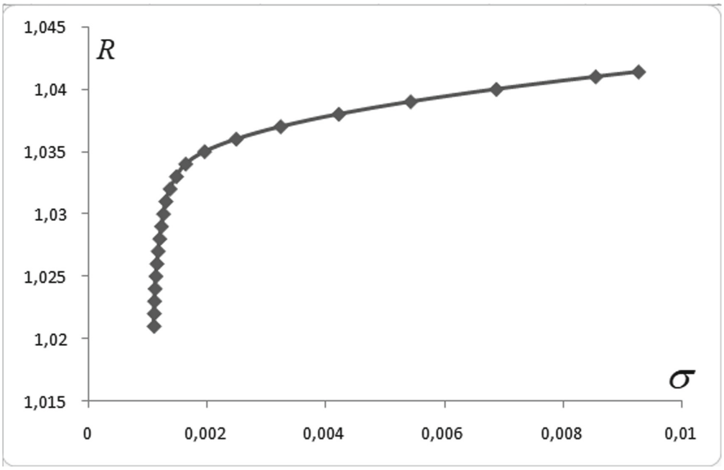

Fig. 2. Efficient frontier of portfolios

The optimal solution yields the weight distribution w_i^*, given in Table 5.

Table 5. Values of R_p, σ_p and the weight distribution w_i^* for efficient portfolios

Portfolio return	Standard deviation	Weights of the assets					
		GMKN	GAZP	MTSS	ROSN	YNDX	SBER
1,041405	0,092685	0,000000	1,000000	0,000000	0,000000	0,000000	0,000000
1,041013	0,083113	0,036501	0,963499	0,000000	0,000000	0,000000	0,000000
1,040012	0,073878	0,129765	0,870235	0,000000	0,000000	0,000000	0,000000
1,039011	0,065123	0,223029	0,776971	0,000000	0,000000	0,000000	0,000000
1,038010	0,057079	0,316294	0,683706	0,000000	0,000000	0,000000	0,000000
1,037010	0,050066	0,409465	0,590535	0,000000	0,000000	0,000000	0,000000
1,036010	0,044407	0,489734	0,498674	0,000000	0,000000	0,011592	0,000000
1,035010	0,040615	0,541632	0,409682	0,000000	0,000000	0,048686	0,000000
1,034010	0,038678	0,593523	0,320703	0,000000	0,000000	0,085774	0,000000
1,033009	0,037245	0,594139	0,269286	0,000000	0,000000	0,090554	0,046021
1,032008	0,036273	0,573069	0,233760	0,000000	0,000000	0,081668	0,111504
1,031008	0,035707	0,552019	0,198269	0,000000	0,000000	0,072791	0,176921
1,030007	0,035226	0,529693	0,179983	0,000000	0,024634	0,068374	0,197316
1,029007	0,034799	0,506621	0,172262	0,000000	0,064310	0,066693	0,190113
1,028006	0,034427	0,483526	0,164533	0,000000	0,104026	0,065012	0,182904
1,027005	0,034114	0,460431	0,156803	0,000000	0,143742	0,063330	0,175694
1,026004	0,03386	0,437336	0,149074	0,000000	0,183458	0,061648	0,168484
1,025004	0,033666	0,414264	0,141353	0,000000	0,223134	0,059968	0,161281
1,024003	0,033529	0,390908	0,133585	0,000891	0,262618	0,058168	0,153830
1,023002	0,033444	0,363136	0,125176	0,016830	0,298175	0,054371	0,142311
1,022001	0,033412	0,335364	0,116766	0,032769	0,333733	0,050575	0,130793

The optimal solution w_i^* has been obtained using the Optimization Toolbox of Excel and the Visual Basic Editor.

3.2 Portfolio Selection Using Performance Evaluation Criteria

We have determined portfolio parameters for the weight distribution w_i^* obtained in Sect. 3.1. We have evaluated portfolio performance using the Sharpe coefficient for a portfolio $RVAR_p$, the Treynor coefficient for a portfolio $RVOL_p$, modified Sharpe coefficients for a portfolio S_{plow}- and S_{pVaR}-coefficients using (15), (16), (23) and (24), respectively. The coefficient S_{pVaR} has been calculated for the confidence levels $\alpha = 0.05$ and $\alpha = 0.1$ to assess different risk preferences. The results are shown in Table 6.

Table 6. Portfolio performance evaluation

Portfolio return	Standard deviation	Portfolio performance evaluation criteria				
		$RVAR_p$	$RVOL_p$	S_{plow}	S_{pVaR}, $\alpha = 0.05$	S_{pVaR}, $\alpha = 0.1$
1,041405	0,096502	0,370464	0,024843	0,558771	0,332226	0,385877
1,041013	0,092685	0,381492	0,025146	0,584157	0,338014	0,397042
1,040012	0,083113	0,413387	0,025987	0,651472	0,359534	0,415895
1,039011	0,073878	0,451514	0,026943	0,704395	0,390774	0,443927
1,038010	0,065123	0,496838	0,028037	0,784864	0,416513	0,474546
1,037010	0,057079	0,549336	0,029303	0,863991	0,442654	0,517757
1,036010	0,050066	0,606315	0,030687	0,881075	0,480951	0,583787
1,035010	0,044407	0,661054	0,032077	0,936465	0,550201	0,622679
1,034010	0,040615	0,698153	**0,033711**	1,008067	0,568637	**0,665058**
1,033009	0,038678	0,707250	0,033038	**1,027810**	**0,575546**	0,648830
1,032008	0,037245	**0,707572**	0,031351	0,983435	0,559560	0,624191
1,031008	0,036273	0,698974	0,029715	0,960907	0,542172	0,606034
1,030007	0,035707	0,682019	0,028597	0,931563	0,524683	0,590323
1,029007	0,035226	0,662941	0,027761	0,899593	0,503408	0,579099
1,028006	0,034799	0,642318	0,026903	0,880509	0,477822	0,560793
1,027005	0,034427	0,620172	0,026024	0,846068	0,468455	0,542368
1,026004	0,034114	0,596530	0,025122	0,809646	0,463934	0,515989
1,025004	0,03386	0,571470	0,024197	0,760013	0,436258	0,491975
1,024003	0,033666	0,545022	0,023240	0,724495	0,421739	0,468593
1,023002	0,033529	0,517397	0,022146	0,673269	0,399149	0,446927
1,022001	0,033444	0,488779	0,021034	0,649726	0,367799	0,423365
1,021000	0,033412	0,459286	0,019904	0,611969	0,343841	0,399553

It is notable, that $RVAR_p$-, $RVOL_p$-, S_{plow}- and S_{pVaR}-coefficients demonstrate a similar trend achieving a maximum value, as shown in Fig. 3. Thus we can assume that introduced portfolio performance criteria enable to select a portfolio with the highest risk premium per unit of risk, measured as deviation of a portfolio return from its 'low-mean' return, or portfolio return from its VaR-return in S_{plow} and S_{pVaR}, respectively. Whereas $RVAR_p$- and $RVOL_p$ coefficients assess risk premium per unit of risk measured by standard deviation and portfolio 'beta', respectively.

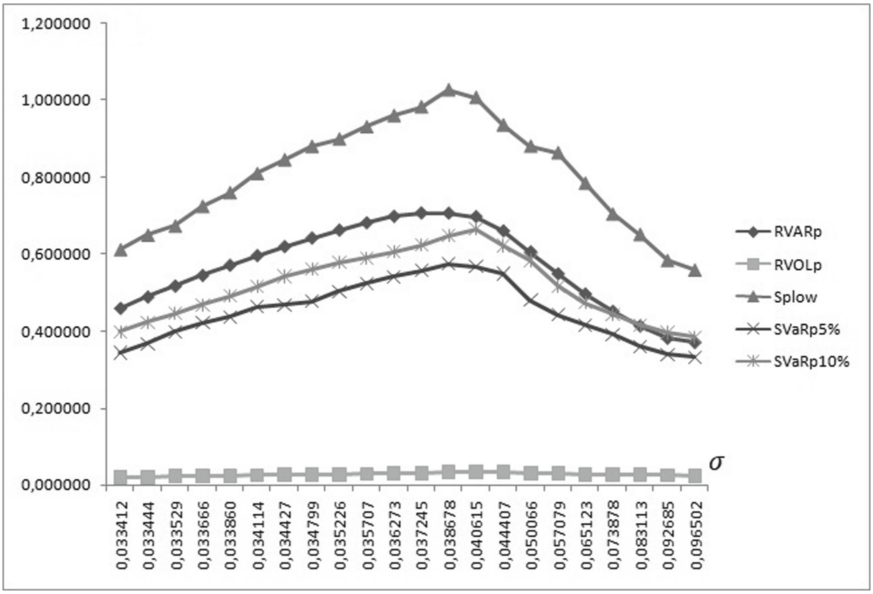

Fig. 3. Portfolio performance evaluation criteria

The portfolios having the maximum values of the $RVAR_p$-, $RVOL_p$-, S_{plow}- and S_{pVaR}-coefficients have been determined. Note, that $RVOL_p$- and S_{pVaR}-criteria for the confidence level $\alpha = 0.1$ indicate the portfolio with the same weight distribution. S_{plow}- and S_{pVaR}-criteria for the confidence level $\alpha = 0.05$ also indicate the portfolio with the same weight distribution. Whereas $RVAR_p$-criterion produces a different weight distribution. Thus, three portfolios, i.e. three weight distributions, have been selected for further approbation.

3.3 Portfolio Testing

In traders' practice it is commonly used to compare the portfolio mean-return with the return of the market to test applicability of the portfolio. An investment portfolio is considered to be efficient if its return is not less than the return of the market.

We consider the return on the *IMOEX* index - the official Moscow Stock Exchange benchmark - to be the market return. The returns on investment portfolios selected in Sect. 3.2 have been compared with the market return. To evaluate their efficiency the monthly-moving portfolio returns and market returns were determined daily for a one-month period, namely January 2020.

Figure 4 shows the returns on the three selected portfolios compared with the returns on the *IMOEX* Index.

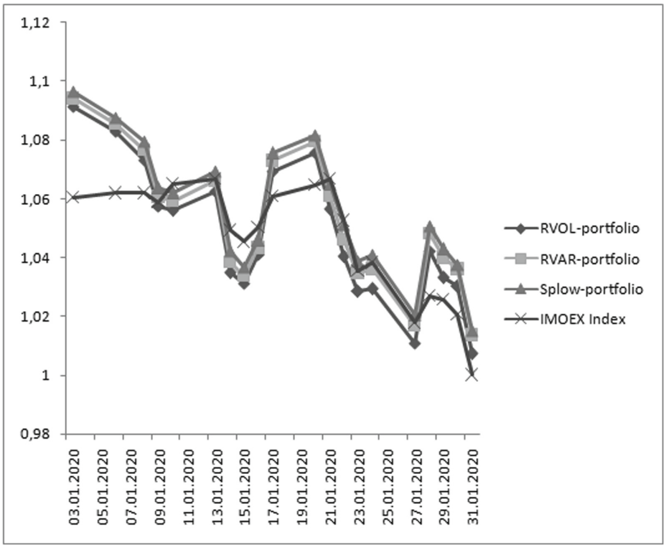

Fig. 4. Returns on the $RVOL_p$-, $RVAR_p$- and S_{plow}-portfolios relatively to the market return (*IMOEX* Index)

To compare the tested portfolio we evaluated portfolio mean return R_p, portfolio standard deviation σ_p, the sum of excessive portfolio return over the market S+, the sum of excessive portfolio return over the market per sum of total deviations from the market (S+/S).

The parameters for the tested portfolios are shown in Table 7.

Table 7. Portfolio and market parameters for a test-period (January 2020)

Portfolio	Portfolio test parameters			
	R_p	σ_p	S+	S+/S
$RVOL_p$	1,047683	0,023272	0,122082	0,553952
$S_{pVaR}(\alpha = 0.1)$	1,047683	0,023272	0,122082	0,553952
$RVAR_p$	1,052124	0,022227	0,164661	0,759838
S_{plow}	1,055105	0,022054	0,199296	0,880431
$S_{pVaR}(\alpha = 0.05)$	1,055105	0,022054	0,199296	0,880431

Note, that the portfolio selected according to $RVOL_p$-criterion (its weight distribution is the same as for S_{pVaR}-criterion $(\alpha = 0.1)$, as has been shown in Sect. 3.2) demonstrate lower mean return and higher risk level.

Portfolio selected according to $RVAR_p$- and S_{plow} - criteria produced better results. The highest excessive return over market return was produced by portfolio selected according to S_{plow}-coefficient. Weight distribution for the portfolio, selected according to S_{plow}-criterion, is the same as for S_{pVaR}-criterion for the confidence level $\alpha = 0.05$.

4 Discussions

The applied the $RVAR_i$-, $RVOL_i$-, S_{ilow}- and S_{iVaR}-coefficients for the assets have yielded almost the same results indicating the most efficient assets in their ranking. While the applied $RVAR_p$-, $RVOL_p$-, S_{plow}- and S_{pVaR}-coefficients for portfolio performance produced different results.

In the case study the portfolio selected according to $RVAR_p$- and S_{plow} - criteria produced better results. The highest excessive return over market return was produced by portfolio selected according to S_{plow}-coefficient. Portfolios selected according to $RVOL_p$-coefficient and S_{pVaR}-criterion $(\alpha = 0.1)$ demonstrated lower mean return and higher risk level, thus they did not prove their applicability in practice.

The experimental study of S_{pVaR}-criterion for confidence level $\alpha = 0.05$ yields better results than for $\alpha = 0.1$. It can be further recommended to apply other methods for VaR computation. Considering the inconsistency of parametric VaR-methods with the stock market of the developing countries, simulation methods are preferable. In the present paper we have used the method of historical modeling. We suppose that other simulation methods could increase the efficiency of the VaR-approach. For example, Monte Carlo simulation, which is widely used in practice.

Thus we can conclude that the proposed modified S_{plow}-coefficient enables to perform portfolio efficiency evaluation, to select a portfolio from the efficient frontier and to achieve better portfolio parameters relatively to other criteria that do not take into account downside risk measures. There is a strong likelihood that it is more adjusted to unstable markets in order to measure risk of the assets and of the portfolio.

S_{plow}-coefficient can be incorporated into the system of key performance indicators for assessing the personnel efficiency, as it reveals the particular achievements of the financial manager and can serve as the basis for building a differentiated wage system.

5 Conclusion

In this paper new S_{ilow}- and S_{iVaR}-securities selection criteria have been proposed, based on the introduced $(\overline{R}_i - R_{ilow})$- and $(\overline{R}_i - VaR_i)$-risk-measures.

$(\overline{R}_i - R_{ilow})$-value can be a suitable risk-measure especially for the asymmetric distribution of the return of an asset. $(\overline{R}_i - VaR_i)$-value allows the investor to set acceptable deviation of the return from the VaR-value for different confidence levels, considering his risk preferences.

S_{plow}- and S_{pVaR}-coefficients have been introduced for portfolio performance evaluation. The modified coefficients may be recommended to evaluate especially the portfolio characterized by asymmetric distribution, which is typical to emerging markets economy and implies increased investment risk.

The case study for portfolio selected according to $RVAR_p$- and S_{plow} - criteria produced better results. To the best of our knowledge the highest excessive return over market return was produced by portfolio selected according to S_{plow}-coefficient. Portfolios selected according to $RVOL_p$- and S_{pVaR}-criteria did not prove their applicability in practice.

The proposed modified S_{plow}-coefficient enables to perform portfolio efficiency evaluation, to select a portfolio from the efficient frontier and to achieve better portfolio parameters.

The proposed modified Sharpe coefficients and computational techniques enable to process financial and labor data, to formalize personnel evaluation process and therefore to increase management efficiency.

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