

Performance measures and investment decisions: evidence from international stock markets

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Abstract: This article investigates the efficacy of various selection criteria to refine the stocks with the best characteristics out of a big pool to facilitate investment decisions. It utilises the performance ratios, namely, the Sharpe ratio, Sortino ratio, and Rachev ratio, as selection criteria to shortlist the assets with the maximum value of these ratios in the in-sample period. We constitute a naive (equal-weighted) portfolio from the shortlisted stocks and analyse their out-of-sample performance across different sizes of the in-sample and out-of-sample periods. The study carries out several experiments on eight stock market datasets selected across the globe. The empirical findings suggest that these selection criteria are relevant because they dominate the benchmark index when their out-of-sample returns are analysed based on several performance measures. The Rachev ratio-based shortlisting criterion outperforms the portfolios obtained from the other performance measures-based selection strategy and the index returns.

Keywords: performance measures; portfolio selection; naive portfolio; international stock markets.

Reference to this paper should be made as follows: Pasricha, L. and Dhanda, N. (2022) 'Performance measures and investment decisions: evidence from international stock markets', *Int. J. Financial Markets and Derivatives*, Vol. 8, No. 3, pp.290–313.

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1 Introduction

One of the most recurrent problems in finance is the problem of asset selection and portfolio management. Financial markets have become highly competitive and information-driven in the past few years that even a tiny packet of supplementary information carries a significant value to an investor. Consequently, every investor tries to design several criteria for asset selection, which will beat the benchmark index when the selected assets constitute a portfolio.

Several approaches, such as clustering, screening based on the historical performance of various measures, etc., have been proposed in the literature to address the asset selection problem. For instance, Larsen and Resnick (1998) demonstrated that tracking portfolios constructed from high-capitalisation stocks perform better than the portfolio obtained from low-capitalisation stocks, thus, showing that the selection process have a significant impact on performance of the tracking portfolio. Alexander and Dimitriu (2004) applied principal component analysis (PCA) on the stock returns to select an optimal tracking portfolio. Focardi and Fabozzi (2004) applied Euclidean distance between time-series of prices, which then was supplied to a clustering technique to compose an optimal tracking portfolio. Dose and Cincotti (2005) utilised a time series clustering approach to restrict the universe of assets to a reasonably limited number and then obtained an optimal portfolio consisting of these assets. Tola et al. (2008) investigated the sensitivity of portfolio optimisation procedure to several filtering criteria based on correlation coefficient matrix. van Montfort et al. (2008) also focussed on the stocks with the highest market capitalisation. Nanda et al. (2010) presented a data mining approach to classify stocks into clusters and then select assets from these clusters to make a portfolio. Other selection procedures are based on so-called screening rules where a pre-specified number of stocks are chosen based on some characteristics in the training period. León et al. (2019) analysed the performance of portfolios constructed using different performance measures such as Sharpe ratio, value-at-risk ratios, etc. Song et al. (2017) applied statistical learning to rank algorithms to select stocks based on the investor's sentiment towards these stocks. In particular, they used sentiment shock and trend indicators to design screening rules. Sant'Anna et al. (2017) investigated co-integration and correlation methods for index tracking (IT) and enhanced indexing (EIT) strategies and studied their out-of-sample performance on Brazilian and US market data. Recently, Goel et al. (2020) used topological data analysis (TDA) to filter the stocks that will beat the index, the strategy known as enhanced indexing. Peykani et al. (2020) introduced a robust two-phase approach for portfolio construction problem by using data envelopment analysis (DEA) as the first step to select assets, followed by solving robust optimisation models for portfolio formation on selected assets.

In this article, we design selection strategies based on several performance measures intending to beat the benchmark. More specifically, firstly, we divide the study period into in-sample and out-of-sample periods and sort the assets based on the values of Sharpe ratio, Sortino ratio, and Rachev ratio calculated in the in-sample period. Second, we select a pre-specified number of stocks with the maximum value of these ratios and form a naive portfolio (equal-weighted). Finally, we analyse the out-of-sample performance of these portfolios' to investigate how these portfolios perform compared to the benchmark index. The idea to use the naive strategy and not solving any portfolio optimisation problem, such as the Markowitz portfolio, is motivated by the empirical studies in Haley (2016) and Haley (2017) that demonstrate that naive portfolio beats the

out-of-performance of optimal portfolios obtained from the optimisation model in the long run.

This study, in particular, considers eight global indices and calculates the three performance measures for all their constituents at the end of the in-sample period. The strategy mentioned above is applied to select the top 25% of the index's constituent assets. We refer Goel et al. (2020) for choosing this particular value. Moreover, we also tried for $p = 10\%, 15\%, 20\%, 30\%$ and observed a similar behaviour for the portfolios constructed. Taking $p = 25\%$ is reasonable as well in the sense that it would be enough to create a sparse and diverse portfolio. We then track the three naive portfolios' performance based on each of the ratios and compare it to the benchmark index. Further, to bring robustness into our conclusions, we adopt the sliding window approach by playing with different in-sample and out-of-sample combinations. We observe that the proposed selection strategies improve the portfolios' performance relative to the benchmark index. Furthermore, the Rachev ratio-based shortlisting criterion outperforms the portfolios obtained using other criteria.

The remainder of this article is organised as follows. Section 2 discusses the performance measures adopted in this study to filter out the assets. Section 3 describes the sample data and the methodology adopted for empirical analysis. Section 4 presents the empirical results and further analyses the significance of the proposed selecting strategies by comparing their out-of-sample returns to the benchmark index returns. Section 5 concludes the article with some directions for future research.

2 Selection criteria and performance measures

This section presents the three performance measures utilised in this study to shortlist the assets for portfolio formation. Three performance measures for each constituent of the index in the in-sample period are calculated, and a pre-defined (see Section 4 for more details on methodology) number of constituents are then selected. These three performance measures are selected such that different characteristics of the returns series can be addressed. The Sharpe ratio depends on the standard deviation and hence focuses on the both sides (profit and loss) of the return series. However, for investment decisions, it is the downside deviation that worries an investor. A portfolio can have a low value of Sharpe ratio but an excellent risk-adjusted out-of-sample return. This is the case when higher standard deviation (low Sharpe ratio) is mainly due to large positive (upside potential) returns. Therefore, one needs to focus on the measures that capture the downside potential and Sortino ratio is one such choice. Furthermore, Sharpe and Sortino ratios do not capture the tail behaviour of the returns and hence are not able to capture the extreme negative returns. This motivates the use of Rachev ratio which can capture the tail losses as the tails of returns are important refer Grody et al. (2013). Before we move to methodology and results, we give the definitions of these three ratios (refer Bacon, 2011) for more details on the definitions. Let $w = (w_1, w_2, \dots, w_N)$ is the portfolio consisting of N assets and r_f denotes the risk-free rate. Denote by $E(w)$ as the mean return of the portfolio over a horizon $[0, T]$, and is given by

$$E(w) = \frac{1}{T} \sum_{i=1}^n \sum_{j=1}^T w_i r_{ij},$$

where r_{ij} represent the return of i^{th} asset in the j^{th} period.

2.1 Sharpe ratio

Sharpe ratio (SR) is the average return earned in excess of the risk-free rate per unit of volatility as measured by the standard deviation and is defined as:

$$SR = \begin{cases} \frac{E(w) - r_f}{\sigma(w)} & E(w) > r_f \\ 0 & E(w) \leq r_f. \end{cases}$$

where $\sigma(w)$ is the standard deviation of portfolio returns.

2.2 Sortino ratio

Sortino ratio is the ratio of mean return in excess of the risk-free rate to the downside deviation. It is defined by

$$\text{Sortino ratio} = \begin{cases} \frac{E(w) - r_f}{\sqrt{\sum_{t=1}^T \frac{[-(-x_t + r_f)^+]^2}{T}}} & E(w) > r_f \\ 0 & E(w) \leq r_f. \end{cases}$$

where x_t is the t^{th} realisation, $t = 1, \dots, T$, of portfolio w , and r_f is the risk free return, and $\xi^+ = \max\{0, \xi\}$.

2.3 Rachev ratio

Rachev ratio (RR) is defined as follows:

$$RR_{\alpha_1, \alpha_2} = \frac{CVaR_{\alpha_1}(w)}{CVaR_{\alpha_2}(-w)}, \quad \alpha_1, \alpha_2 \in (0, 1).$$

Here, $CVaR_{\alpha}(w)$ (refer Appendix for definition of CVaR) is conditional value at risk of the portfolio w at the significance level α . Intuitively, this ratio allows a trade-off between potential of extreme positive returns to the risk of extreme losses.

3 Data and methodology

This section presents the details of the indices used, and the methodology followed in the empirical analysis.

3.1 Sample data

We consider eight global indices for the empirical analysis. These indices are selected, aiming to include developing and developed countries in the investigation during the corresponding period of study. Besides, this selection of indices allows us to perform extensive empirical experiments to test the efficacy and robustness of the methodology considered in this article. We obtain the daily closing prices of the indices and their

constituents from the Thomson Reuters EIKON data stream. Since the composition of any index is dynamic, i.e., it does not remain the same over time; therefore, to avoid any impact of inclusion or exclusion of a constituent in the index, we restricted our analysis to those periods where the maximum number of component assets are available. Table 1 gives the list of indices, their total number of constituents, and the number of constituents considered for this study. Finally, the study period for the first six indices starts from January 2005 till November 2018 (number of observations per index is 3,625). The period for the last two indices is from January 2010 to November 2018 (the number of observations per index is 2,320).

Table 1 Indices used for empirical analysis

No.	Index	Country	No. of constituents	Constituents considered
1	Dow Jones Industrial Average (DJIA)	USA	30	28
2	Topix core 30 (Topix)	Japan	30	29
3	DAX 30	Germany	30	27
4	Athex composite (Athex)	Greece	60	53
5	Sensex	India	30	28
6	CNX	India	50	41
7	IBovespa (Bovespa)	Brazil	60	57
8	Hang-Seng	Hong Kong	50	46

3.2 Methodology

The article follows the convention of working with log returns, obtained using the closing prices, in the literature on portfolio optimisation and investment decisions. The daily log-returns are calculated as follows:

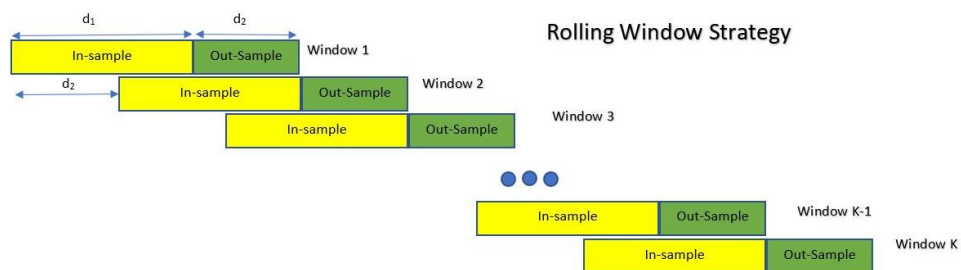
$$x_{it} = \ln\left(\frac{S_{it}}{S_{it-1}}\right), \quad i = 1, \dots, n, \quad t = 1, \dots, T,$$

where S_{it} and S_{it-1} denote the closing prices of the i^{th} stock on the t^{th} day and $(t-1)^{\text{th}}$ day respectively.

For illustration purposes, we consider only one index. However, the same methodology is applied to each index while performing the experiments. We adopt the sliding window approach with different in-sample and out-of-sample combinations for the analysis. More specifically, assume that the index consists of a data period of size N (note that $N = 3,625$ for the first six indices and 2,320 for the last two). The article considers an in-sample period of length d_1 days, i.e., $1, 2, \dots, d_1$ to create the portfolios based on the proposed strategy (see Table 2) and then, tests the performance of the portfolio on an out-of-sample data of length d_2 , i.e., $d_1 + 1, \dots, d_1 + d_2$. Then, the in-sample period is shifted by d_2 days, i.e., the new in-sample is $1 + d_2, 2 + d_2, \dots, d_1 + d_2$ based on which the portfolio is created, followed by an assessment of its performance in the new out-of-sample period, i.e., $d_1 + 1 + d_2, d_1 + 2 + d_2, \dots, d_1 + d_2 + d_2$. We repeat this exercise by shifting the periods by d_2 days until the whole data period is exhausted. Figure 1 illustrates the rolling window approach.

Table 2 Different combinations of d_1 and d_2 and number of windows for each combination

d_1	d_2	Number of out-of-sample windows	
		datasets 1–4	dataset 5–6
$5 \times 12 \times 21$	$2 \times 12 \times 21$	4	2
$2 \times 12 \times 21$	$1 \times 12 \times 21$	12	7
$1 \times 12 \times 21$	$0.5 \times 12 \times 21$	26	16
$0.5 \times 12 \times 21$	$\frac{1}{12} \times 12 \times 21$	166	104

Figure 1 Description of rolling window approach (see online version for colours)

At the end of each in-sample period, the three ratios, namely the Sharpe ratio, Sortino ratio, and Rachev ratio, are estimated for each constituent of the index based on the daily returns in the in-sample period. Then, we rank the constituents in the decreasing order of each measure, and we select the top 25% of the total number of constituents. We highlight here that when 25% of the constituents are less than 10 (for instance, in DAX 30), we select the top 10 stocks. After selecting the stocks based on the three measures, three portfolios are obtained¹, one for each measure. These portfolios are denoted by $C1$, $C2$ and $C3$ respectively. More specifically, the portfolio $C1$ consists of the top 25% of the constituents with the maximum value of the Sharpe ratio in the in-sample period. Similarly, $C2$ and $C3$ consist of the top 25% of the constituents with the maximum value of the Sortino ratio and Rachev ratio respectively. Finally, the portfolio returns are calculated over the out-of-sample period and are analysed based on various characteristics. We repeat the same exercise for all windows and all the indices. We present the results and analysis of the experiments in the next Section.

Also, four different combinations of in-sample and out-of-sample periods, i.e., (d_1, d_2) , are analysed to make our analysis robust with respect to the choice of (d_1, d_2) and to provide us with the definite conclusions. Table 2 presents the different pairs (d_1, d_2) considered in this study. In this table, $d_1 = 5 \times 12 \times 21$ means 5 years, 12 months and 21 days per month, i.e., 1,260 observations. Similarly, the other combinations.

Remark 1: In the experiments, the risk-free rate is considered to be zero.

4 Empirical results

4.1 Markets other than Indian market

Tables 3 to 10 present the out-of-sample performance of the three portfolios obtained for the indices other than Sensex and CNX. The results are presented for different combinations of (d_1, d_2) including the window wise analysis.

4.1.1 Description of analysis

4.1.1.1 Mean returns

Except for the indices DJIA and DAX, we observe that portfolio C3 produces the highest mean returns compared to portfolios C1 and C2. Further, we observe that portfolio C3 never attains the worst returns (see the minimum value). This observation suggests that portfolio C3 prevents the investor from suffering significant losses. It is worth noting that the three portfolios' mean return is higher than that obtained by the index for all the markets studied. Also, the mean values of the three portfolios are negative only for the ATHEX market. In contrast, the mean values for the indices are negative for two markets, namely, ATHEX and Topix. Therefore, we conclude that the proposed portfolio selection strategy outperforms the index in terms of mean returns.

4.1.1.2 Risk measures

Next, we compare the portfolios' performance based on the risk measures, namely, standard deviation (Std Dev), mean absolute deviation (MAD), semi deviation (Semi Dev), value at risk (VaR), conditional value at risk (CVaR) and downside deviation (DD). An investor desires the portfolios with a minimum value of the risk measures. We observe that the silver lining of portfolio C3 is that it produces the least risk compared to portfolios C1 and C2. Hence, we conclude that portfolio C3 is well suited for risk-averse investors. Furthermore, we observe that the values of risk measures for portfolio C1 fall between the corresponding values for portfolios C2 and C3 for all the indices except the ATHEX.

4.1.1.3 Reward risk ratios

- 1 Sharpe and Sortino's ratios are the ratio of the mean return to Std Dev and DD, respectively. In other words, these are mean risk ratios. The analysis reveals that portfolio C3 excels in terms of these ratios for all the indices. Further, all the portfolios produce a high value of these ratios compared to the benchmark index. Also, it is worth noting that C1 results in the worst values in 80% of the cases compared with C2 and C3, i.e., C2 lies in between C1 and C3 in terms of the mean risk ratios considered in the study. It is intuitive in the sense that C1 penalises positive returns while C2 penalises only the losses since the Sortino ratio focuses on the downside risk in contrast to the Sharpe ratio that focuses on both downside and upside deviations.
- 2 On the other hand, the Rachev ratio is a tail ratio, i.e., it is the ratio of the right tail to the left tail of returns (ratio of profits to losses). We observe that portfolio

C2 outperforms the other portfolios in terms of the Rachev ratio. Further, in most cases, the selected portfolios outperform the index in terms of this ratio.

It is worthy to note that, although C2 focuses on maximising the in-sample Sortino ratio and C3 focuses on maximising the in-sample Rachev ratio, the out-of-sample results are pretty different. The out-of-sample performance is just the reverse of this. More specifically, C2 portfolios produce the highest out-of-sample Rachev ratio, whereas C3 portfolios give the highest out-of-sample Sortino ratios. This observation indicates an out-of-sample change in the distribution of asset returns, suggesting a need to switch to a robust version for portfolio construction.

In conclusion, from Table 3 and the observations mentioned above, we can conclude the following

- The distributional properties of the out-of-sample returns generated by the three different portfolio selection strategies differ significantly from each other. More specifically, portfolio C1 consists of the assets with maximum Sharpe ratio in the in-sample period. But analysis of Table 3 indicates that it does not have the maximum Sharpe ratio in the out-of-sample period. Similarly, portfolios C2 and C3 do not have the maximum Sortino and Rachev ratios in the out-of-sample period. This observation demonstrates that the return distribution is different for in-sample and out-of-sample periods, as one would expect.
- The portfolios constructed using the screening rules based on the Sharpe, Sortino, and Rachev ratios perform better than the benchmark index, and the selection based on Rachev ratio seems to be the most appropriate selection strategy.
- From an investor's point of view, he could invest in C2 or C3 depending on his risk preferences. Portfolio C3 is typically preferable for risk-averse investors, whereas portfolio C2 is for the risk seekers who wish to obtain higher tail ratios.

4.1.1.4 Robustness check

We further analyse the performance of the three portfolios, C1, C2, and C3, to confirm that the above conclusions are robust and consistent. We re-perform the previous exercise for different pairs of in-sample and out-of-sample periods, i.e., the pair (d_1, d_2) . Tables 4 to 6 present the results of the experiments with two years and one year, five years and two years, and six months and one-month in-sample and out-of-sample periods. The study does not discuss each Table in detail here. Still, one can observe that the conclusions similar to the case of 1-year in-sample and six months out-of-sample period (i.e., Table 3) can be drawn, confirming that the results are robust in the sense that they are independent of the choice of (d_1, d_2) .

To make the analysis robust, the study further observes the out-of-sample performance of the portfolios in each window. For this case, the article only presents the results for the case of 5 years and two years in-sample and out-of-sample periods (see Tables 7 to 10) since for this choice of (d_1, d_2) , the number of windows is small, which makes it feasible to include these results in this article. Out of 21 windows, the same conclusion is drawn that C3 performs the best in around 15 windows. Although the index is less risky in some windows compared to the portfolio C3, however, if we observe the performance, portfolio C3 provides the best results in the long run.

Table 3 This table presents the performance of the portfolios in the out-of-sample period in the case when in-sample period size is 1 years and out-of-sample size is 6 months (values are $\times 10^{-3}$)

	BOVESPA			DAX			ATHEX			Hang seng		
	C1	C2	Index	C1	C2	Index	C1	C2	Index	C1	C2	Index
Mean	0.043	0.057	0.021	0.127	0.138	0.111	0.127	0.138	0.127	0.120	0.120	0.029
Minimum	-51.952	-51.952	-40.003	-39.834	-39.834	-32.300	-39.834	-39.834	-36.587	-33.794	-33.794	-26.137
Maximum	22.825	24.402	27.740	50.187	50.187	46.900	50.187	50.187	51.484	22.200	22.200	23.967
Standard deviation	6.166	6.225	6.116	6.115	6.128	5.876	6.115	6.128	5.367	4.955	4.822	3.424
Mean absolute deviation	4.484	4.503	4.520	4.132	4.145	4.018	4.132	4.145	3.685	3.630	3.630	3.526
Semi-deviation	4.468	4.507	4.360	4.484	4.492	4.249	4.484	4.492	3.938	3.826	3.826	3.347
Sortino ratio	9.616	12.823	4.779	28.604	31.232	26.475	28.604	31.232	32.858	28.457	28.457	6.078
Sharpre ratio	6.934	9.225	3.398	20.707	22.570	18.907	20.707	22.570	23.748	17.893	17.893	11.607
CVaR	14.149	14.300	13.508	15.265	15.268	14.109	15.265	15.268	13.067	12.130	12.130	7.785
VaR	10.137	10.089	9.939	9.868	9.866	9.268	9.868	9.866	8.457	8.070	8.070	0.121
Rachev ratio	0.192	0.197	0.181	0.207	0.208	0.185	0.207	0.208	0.151	0.135	0.135	0.121
Downside deviation	4.446	4.478	4.350	4.427	4.428	4.197	4.427	4.428	3.879	3.660	3.660	3.511
<i>ATHEX</i>												
Mean	-0.160	-0.164	-0.175	0.090	0.104	0.029	0.090	0.104	0.120	0.120	0.120	0.029
Minimum	-81.211	-83.126	-76.926	-30.111	-33.794	-25.300	-30.111	-33.794	-25.300	-25.300	-25.300	-26.137
Maximum	58.843	58.843	58.330	27.393	33.128	23.967	27.393	33.128	22.200	22.200	22.200	23.967
Standard deviation	7.966	7.836	8.524	5.036	5.098	4.822	5.036	5.098	4.955	4.822	4.822	3.424
Mean absolute deviation	5.345	5.261	5.828	3.567	3.588	3.424	3.567	3.588	3.630	3.630	3.630	3.526
Semi-deviation	5.865	5.783	6.212	3.660	3.710	3.600	3.660	3.710	3.600	3.600	3.600	3.347
Sortino ratio	-26.871	-28.060	-27.733	24.915	28.457	26.475	24.915	28.457	33.826	28.457	28.457	6.078
Sharpre ratio	-20.031	-20.979	-20.480	17.893	20.432	17.893	17.893	20.432	24.168	17.893	17.893	11.607
CVaR	19.894	19.538	20.659	12.007	12.130	11.607	12.007	12.130	11.563	11.563	11.563	7.785
VaR	12.780	12.535	13.912	7.892	8.070	7.892	7.892	8.070	7.868	7.868	7.868	0.121
Rachev ratio	0.352	0.339	0.392	0.132	0.135	0.121	0.132	0.135	0.123	0.123	0.123	0.121
Downside deviation	5.939	5.858	6.295	3.617	3.660	3.511	3.617	3.660	3.540	3.540	3.540	3.511

Table 3 This table presents the performance of the portfolios in the out-of-sample period in the case when in-sample period size is 1 years and out-of-sample size is 6 months (values are $\times 10^{-3}$) (continued)

	DJIA			Index			TPIX			
	C1	C2	C3	C1	C2	C3	C1	C2	C3	Index
Mean	0.115	0.112	0.110	0.110	0.110	0.110	0.003	0.006	0.022	-0.033
Minimum	-45.788	-45.788	-37.568	-35.614	-48.083	-48.083	-48.083	-48.083	-43.891	-46.844
Maximum	48.517	48.517	51.039	45.637	50.203	50.203	50.203	50.203	47.780	58.756
Standard deviation	5.260	5.271	4.922	4.800	6.259	6.259	6.259	6.270	6.061	6.432
Mean absolute deviation	3.293	3.306	3.133	3.032	4.214	4.214	4.214	4.225	4.126	4.359
Semi-deviation	3.817	3.823	3.527	3.507	4.562	4.562	4.562	4.566	4.419	4.675
Sortino ratio	30.598	29.761	31.758	31.924	0.590	0.590	0.590	1.340	4.906	-7.068
Sharpe ratio	21.917	21.314	22.443	23.014	0.430	0.430	0.430	0.975	3.569	-5.154
CVaR	13.012	13.025	12.041	12.035	15.266	15.266	15.266	15.277	14.641	15.644
VaR	7.711	7.716	7.546	7.270	9.673	9.673	9.673	9.656	9.204	10.156
Rachev ratio	0.158	0.158	0.136	0.131	0.211	0.211	0.211	0.212	0.195	0.222
Downside deviation	3.767	3.775	3.478	3.460	4.561	4.561	4.561	4.563	4.409	4.691

Table 6 This table presents the performance of the portfolios in the out-of-sample period in the case when in-sample period size is 6 months and out-of-sample size is 1 month (values are $\times 10^{-3}$)

	Bovespa			Greece			DJIA			Index	
	C1	C2	C3	C1	C2	C3	C1	C2	C3		
Mean	0.015	0.021	0.022	0.057	0.072	0.136	0.116	-0.139	-0.144	-0.079	-0.149
Minimum	-53.025	-53.025	-41.274	-0.003	-42.797	-33.204	-32.283	-95.535	-95.535	-57.329	-76.926
Maximum	24.599	24.599	27.210	27.740	58.376	43.635	46.893	57.066	57.066	46.504	58.330
Standard deviation	5.768	5.741	5.499	6.083	6.044	5.272	5.767	7.646	7.659	6.964	8.397
Mean absolute deviation	4.190	4.167	3.981	4.502	4.083	3.669	3.946	5.201	5.182	4.784	5.710
Semi-deviation	4.215	4.194	3.936	4.328	4.469	3.863	4.172	5.714	5.707	5.137	6.126
Sortino ratio	3.626	4.921	5.668	13.372	16.307	35.694	28.214	-24.107	-24.872	-15.176	-24.027
Sharpe ratio	2.645	3.587	4.046	9.406	11.969	25.725	20.142	-18.218	-18.746	-11.275	-17.728
CVaR	13.390	13.314	12.457	13.327	15.108	12.746	13.806	19.151	19.251	17.134	20.436
VaR	9.608	9.454	8.912	9.915	9.900	8.555	9.122	12.254	12.618	11.094	13.719
Rachev ratio	0.165	0.164	0.153	0.178	0.195	0.146	0.177	0.313	0.317	0.260	0.384
Downside deviation	4.207	4.184	3.925	4.299	4.436	3.799	4.117	5.778	5.772	5.174	6.196

	DAX			HANG			TOPIX			Index	
	C1	C2	C3	C1	C2	C3	C1	C2	C3		
Mean	0.099	0.099	0.134	0.042	0.152	0.108	0.115	0.012	0.019	0.057	0.006
Minimum	-32.200	-32.200	-25.943	-2.6137	-36.168	-37.099	45.637	-35.61873	-51.343	-47.871	-46.844
Maximum	25.335	26.866	21.590	23.967	49.837	54.559	4.712	48.423	48.423	55.591	58.756
Standard deviation	5.003	5.002	4.965	4.835	4.948	4.841	2.985	6.220	6.247	5.972	6.328
Mean absolute deviation	3.591	3.594	3.627	3.447	3.168	3.101	2.985	4.166	4.183	4.054	4.290
Semi-deviation	3.655	3.649	3.577	3.533	3.556	3.482	3.443	4.519	4.529	4.340	4.605
Sortino ratio	27.347	27.631	38.085	11.959	43.658	43.870	33.866	2.676	4.293	13.299	1.291
Sharpe ratio	19.718	19.886	26.919	8.688	30.793	31.024	24.393	1.942	3.106	9.605	0.939
CVaR	11.714	11.629	11.355	11.562	12.037	11.894	11.802	15.053	15.091	14.352	15.362
VaR	7.755	7.829	7.771	7.849	7.373	7.239	7.128	9.332	9.385	9.158	9.984
Rachev ratio	0.125	0.125	0.124	0.120	0.138	0.131	0.126	0.208	0.210	0.189	0.214
Downside deviation	3.607	3.600	3.509	3.513	3.490	3.434	3.394	4.513	4.520	4.373	4.602

Table 7 This table presents the window-wise performance of the portfolios in the out-of-sample period in the case when in-sample period size is 5 years and out-of-sample size is 2 year (read column wise) (values are $\times 10^{-3}$) (continued)

<i>DAX</i>	<i>w1</i>			<i>w4</i>			<i>Index</i>
	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C1</i>	<i>C2</i>	<i>C3</i>	
Mean	0.074	0.074	0.057	0.103	0.103	0.219	0.119
Minimum	-38.810	-38.810	-29.050	-31.749	-31.749	-22.587	-30.693
Maximum	20.708	20.708	20.822	17.588	17.588	15.350	21.072
Standard deviation	6.047	6.047	5.047	5.440	5.440	5.120	5.382
Mean absolute deviation	4.267	4.267	3.500	3.763	3.763	3.643	3.754
Semi-deviation	4.641	4.641	3.767	4.133	4.133	3.823	3.958
Sortino ratio	16.157	16.157	15.127	25.194	25.194	58.995	30.499
Sharpe ratio	12.310	12.310	11.214	18.927	18.927	42.866	22.115
CVaR	15.403	15.403	12.600	14.040	14.040	12.555	13.170
VaR	9.787	9.787	8.529	9.190	9.190	9.042	8.554
Rachev ratio	0.186	0.186	0.134	0.157	0.157	0.136	0.154
Downside deviation	4.607	4.607	3.741	4.087	4.087	3.720	3.902

Table 8 This table presents the window-wise performance of the portfolios in the out-of-sample period in the case when in-sample period size is 5 years and out-of-sample size is 2 year (read column wise) (values are $\times 10^{-3}$)

GREECE	w1			Index	w4			Index
	C1	C2	C3		C1	C2	C3	
Mean	-0.723	-0.723	-1.054	-1.093	-0.113	-0.113	0.366	0.191
Minimum	-30.023	-30.023	-28.961	-30.039	-43.906	-43.906	-44.082	-62.595
Maximum	51.261	51.261	56.367	58.330	29.531	29.531	37.006	38.942
Standard deviation	7.880	7.880	8.621	9.772	6.953	6.953	5.333	7.869
Mean absolute deviation	5.384	5.388	5.588	7.169	4.666	4.666	3.501	5.076
Semi-deviation	5.384	5.384	5.732	6.534	5.328	5.328	4.032	6.044
Sortino ratio	-123.394	-123.394	-166.702	-152.816	-21.013	-21.013	94.350	32.047
Sharpe ratio	-91.809	-91.809	-122.226	-111.849	-16.253	-16.253	68.601	24.292
CVaR	17.341	17.341	18.225	20.695	18.264	18.264	12.042	19.837
VaR	13.534	13.534	14.770	15.557	11.862	11.862	7.523	12.624
Rachev ratio	0.309	0.309	0.358	0.461	0.258	0.258	0.130	0.322
Downside deviation	5.769	5.769	6.321	7.152	5.378	5.378	3.878	5.964
					HANG (w1)			
Mean	0.360	0.360	0.492	0.252	0.079	0.079	0.061	-0.002
Minimum	-27.633	-27.633	-25.951	-31.992	-22.946	-22.946	-26.421	-26.137
Maximum	20.922	20.922	28.991	41.854	17.578	17.578	22.292	17.463
Standard deviation	7.815	7.815	7.199	9.839	4.875	4.875	5.292	5.355
Mean absolute deviation	5.783	5.783	5.269	7.205	3.482	3.482	3.754	3.855
Semi-deviation	5.766	5.766	5.193	7.114	3.533	3.533	3.840	3.884
Sortino ratio	64.326	64.326	99.424	36.035	22.510	22.510	16.121	-0.422
CVaR	46.001	46.001	68.354	25.591	16.134	16.134	11.606	-0.306
Sharpe ratio	18.517	18.517	16.100	22.461	11.686	11.686	12.640	12.824
VaR	13.564	13.564	11.985	16.890	8.425	8.425	8.821	8.758
Rachev ratio	0.300	0.300	0.257	0.488	0.122	0.122	0.145	0.154
Downside deviation	5.589	5.589	4.949	6.988	3.494	3.494	3.810	3.885

Table 8 This table presents the window-wise performance of the portfolios in the out-of-sample period in the case when in-sample period size is 5 years and out-of-sample size is 2 year (read column wise) (values are $\times 10^{-3}$) (continued)

	w3			w2			Index
	C1	C2	C3	C1	C2	C3	
Mean	-0.323	-0.323	-0.037	0.157	0.157	0.207	0.082
Minimum	-73.163	-73.163	-58.788	-18.894	-18.894	-20.423	-22.809
Maximum	35.557	35.557	32.105	11.385	11.385	12.482	9.730
Standard deviation	9.438	9.438	7.613	3.815	3.815	4.252	3.918
Mean absolute deviation	6.255	6.255	5.038	2.870	2.870	3.211	2.897
Semi-deviation	7.192	7.192	5.631	2.849	2.849	3.180	2.946
Sortino ratio	-44.070	-44.070	-6.562	56.473	56.473	67.134	28.233
Sharpe ratio	-34.245	-34.245	-4.868	41.033	41.033	48.586	20.942
CVaR	23.077	23.077	17.826	9.132	9.132	10.082	9.194
VaR	13.472	13.472	10.191	6.626	6.626	7.047	6.353
Rachev ratio	0.446	0.446	0.291	0.067	0.067	0.085	0.070
Downside deviation	7.334	7.334	5.648	2.772	2.772	3.077	2.906

Table 10 This table presents the window-wise performance of the portfolios in the out-of-sample period in the case when in-sample period size is 5 years and out-of-sample size is 2 year (read column wise) (values are $\times 10^{-3}$)

TOPIX	w1			w2			Index
	C1	C2	C3	C1	C2	C3	
Mean	-0.190	-0.190	-0.015	0.456	0.456	0.378	0.462
Minimum	-33.650	-33.650	-36.056	-29.122	-29.122	-24.221	-26.817
Maximum	23.798	23.798	32.891	23.446	23.446	20.287	23.236
Standard deviation	5.426	5.426	5.474	6.055	6.055	5.525	5.983
Mean absolute deviation	3.881	3.881	3.941	4.521	4.521	4.143	4.554
Semi-deviation	3.951	3.951	3.917	4.296	4.296	3.860	4.191
Sortino ratio	-46.925	-46.925	-3.875	112.211	112.211	103.307	117.074
Sharpe ratio	-34.990	-34.990	-2.778	75.291	75.291	68.457	77.217
CVaR	12.192	12.192	11.936	13.013	13.013	11.564	12.629
VaR	7.873	7.873	7.830	8.522	8.522	7.765	7.955
Rachev ratio	0.136	0.136	0.133	0.171	0.171	0.142	0.165
Downside deviation	4.046	4.046	3.925	4.062	4.062	3.661	3.946
				w3			
Mean	0.388	0.388	0.325	-0.014	-0.014	-0.095	-0.099
Minimum	-19.030	-19.030	-18.545	-33.319	-33.319	-29.580	-33.688
Maximum	17.983	17.983	24.081	35.588	35.588	34.104	35.700
Standard deviation	4.634	4.634	4.585	6.791	6.791	6.246	6.547
Mean absolute deviation	3.360	3.360	3.242	4.482	4.482	4.110	4.333
Semi deviation	3.370	3.370	3.291	4.879	4.879	4.480	4.731
Sortino ratio	121.992	121.992	103.525	-2.808	-2.808	-20.960	-20.739
Sharpe ratio	83.796	83.796	70.789	-2.020	-2.020	-15.181	-15.132
CVaR	10.787	10.787	10.504	16.558	16.558	15.157	16.213
VaR	7.781	7.781	7.515	10.604	10.604	10.267	10.511
Rachev ratio	0.110	0.110	0.106	0.255	0.255	0.218	0.238
Downside deviation	3.183	3.183	3.135	4.886	4.886	4.524	4.777
				w4			
Mean	0.388	0.388	0.222	-0.014	-0.014	-0.095	-0.099
Minimum	-19.030	-19.030	-17.362	-33.319	-33.319	-29.580	-33.688
Maximum	17.983	17.983	19.907	35.588	35.588	34.104	35.700
Standard deviation	4.634	4.634	4.544	6.791	6.791	6.246	6.547
Mean absolute deviation	3.360	3.360	3.277	4.482	4.482	4.110	4.333
Semi deviation	3.370	3.370	3.258	4.879	4.879	4.480	4.731
Sortino ratio	121.992	121.992	70.498	-2.808	-2.808	-20.960	-20.739
Sharpe ratio	83.796	83.796	48.841	-2.020	-2.020	-15.181	-15.132
CVaR	10.787	10.787	10.627	16.558	16.558	15.157	16.213
VaR	7.781	7.781	8.289	10.604	10.604	10.267	10.511
Rachev ratio	0.110	0.110	0.106	0.255	0.255	0.218	0.238
Downside deviation	3.183	3.183	3.148	4.886	4.886	4.524	4.777

Table 11 Out-of-sample performance of the portfolios with 1 year in-sample and 6 months out-of-sample period on the Indian market

	SENSEX			CNX			Index
	CI	C2	C3	CI	C2	C3	
Mean	0.201	0.200	0.228	0.232	0.211	0.200	0.181
Minimum	-43.416	-43.416	-48.779	-44.512	-44.512	-46.065	-56.520
Maximum	61.266	61.266	60.864	54.290	54.290	63.464	70.939
Standard deviation	6.058	6.026	6.520	6.037	5.984	6.385	6.097
Mean absolute deviation	4.202	4.178	4.506	4.202	4.159	4.402	3.999
Semi-deviation	4.351	4.331	4.684	4.393	4.345	4.659	4.388
Sortino ratio	47.266	47.200	49.824	54.132	49.633	43.717	41.932
Sharpe ratio	33.199	33.181	34.970	38.410	35.216	31.265	29.620
CVaR	12.697	12.616	13.719	12.872	12.724	13.762	13.025
VaR	8.085	7.917	8.453	7.890	7.708	8.537	7.680
Rachev ratio	0.156	0.154	0.185	0.155	0.152	0.172	0.162
Downside deviation	4.255	4.236	4.576	4.284	4.246	4.566	4.307

Therefore, summing up the results, we can conclude that portfolio C3 shows robustness and consistency in the long run, and one can use it to hedge against the risk.

4.2 *Indian market*

Table 11 presents the performance of the three portfolios and the index of the Indian market. The study considers CNX Nifty 50 and Sensex 30 as benchmark indices, two major stock market indices in the Indian stock market. The reason for including a separate section for the Indian market is the inconsistency in the three portfolios' performance, unlike the consistency we observed for the indices other than the Indian market, as discussed in the previous sub-section. However, the first two conclusions about the different distributional characteristics of the portfolio returns in the in-sample and out-of-sample period and the portfolios' dominance over the index remain intact.

From Table 11, one could easily observe that the proposed portfolios provide a better trade-off between the risk and the return than the index by attaining the higher values of Sharpe and Sortino ratios. Also, these portfolios deliver a better return than the benchmark index for both the indices considered. However, it is difficult to conclude which selection criterion works best for a risk-averse investor wishing to invest in the Indian market due to the mixed results.

5 **Conclusions**

This study examines the consequences of integrating selection criteria based on three performance ratios into the portfolio formation process. More specifically, this article studies the out-of-sample performance of the naive portfolios formed by the few assets selected (out of all the constituents of a stock index) based on the values of the three performance measures in the in-sample period. This study's central finding is the significant improvement in portfolios' performance constructed using the selection criteria based on the performance ratios. The empirical analysis finds that the portfolios formed based on the proposed selection strategy outperform the corresponding benchmark index when tested on various performance measures for all the global indices except the Indian market.

The complexity of the investment decision problem leads us to propose a further research problem. The present study formed a naive portfolio on the shortlisted stocks. It would be interesting to examine how this selection strategy performs when a portfolio optimisation problem, for example, the Markowitz portfolio, is solved on the selected assets instead of giving equal weights to all of them. One of the significant problems in investment decisions is index tracking (enhanced indexing), where the investor's objective is to track (outperform) the benchmark index. One, of course, can invest in all the constituents of the index and perfectly track the index, but investing in many stocks incur enormous transaction costs. Therefore, one approach is to shortlist the assets such that the portfolio consisting of shortlisted assets tracks (or beat) the benchmark index. Hence, it would be interesting to see how the proposed strategy can be integrated with a portfolio optimisation problem to reduce the tracking error for index-tracking (enhanced indexing).

Finally, we plan to consider the transaction costs in these portfolio optimisation problems by introducing constraint on the transaction cost. Note that in our paper, the

idea is to filter 25% of the assets constituting the index based on some criteria which gives a sparse portfolio that should induce less transaction and monitoring cost and possibly achieve better returns than the naive strategy on all the assets. Since we use naive strategy and compare models on same levels, the results on transaction cost do not impact our analysis.

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Appendix

Here, we briefly explain the performance measures utilised for the out-of-sample analysis. For more details on these measures, interested readers are suggested to refer to Bacon (2011). Let $w = (\frac{1}{n}, \dots, \frac{1}{n})'$, denotes the weights of the portfolio (either C1, C2 or C3) and let I denotes the benchmark index.

Excess mean return

As the name suggests, it is the expected value of the difference between the portfolio return and the index return, i.e., $EMR = E(w) - E(I)$. Clearly, one desires for higher values of excess mean return (EMR).

Value-at-risk

Given a confidence level $\alpha \in (0, 1)$, VaR_α is the maximum possible loss of the portfolio and it is defined as:

$$VaR_\alpha(-w) = \min\{r \in \mathbb{R} \mid F_{-w}(r) = Pr(-w \leq r) \geq \alpha\},$$

where $F_{-w}(r)$ denotes the cumulative distribution function of the portfolio loss.

Condition value at risk

It measures the expected losses in the portfolio that are beyond $VaR_\alpha(-w)$. More specifically, it is the mean of the α -tail distribution of $-R(w)$ where the α -tail distribution of $-R(w)$ is described as follows:

$$G_\alpha(-R(w), r) = \begin{cases} 0, & r < VaR_\alpha(-R(w)) \\ \frac{F_{-R(w)}(r) - \alpha}{1 - \alpha}, & r \geq VaR_\alpha(-R(w)) \end{cases}.$$

Mean absolute deviation

It is defined as

$$MAD = \frac{\sum_{j=1}^T |(w_i r_{ij} - E(w))|}{T}.$$

Semi-deviation

It depicts the under-achievement of the portfolio from its mean return and is given by

$$\text{Semi Dev} = \sqrt{\sum_{j=1}^T \frac{((E(X) - X_j)^+)^2}{T}}.$$

The lower values are preferable.

Downside deviation

It depicts under achievement of portfolio from the benchmark or the risk free return. It is given by

$$DD = \sqrt{\sum_{t=1}^T \frac{((r_f - x_t)^+)^2}{T}}.$$

The lower values are preferable.

VaR ratio

It is the same as Rachev ratio with VaR measure replacing the CVaR in the ratio.