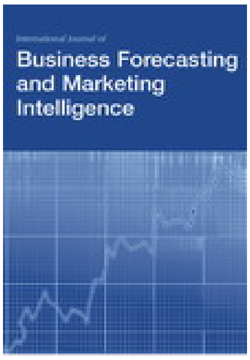

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A study on the performance evaluation of equal-weight portfolio and optimum risk portfolio on the Indian stock market

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Abstract: Designing an optimum portfolio for allocating suitable weights to its constituent assets so that the return and risk associated with the portfolio are optimised is a computationally hard problem. The seminal work of Markowitz that attempted to solve the problem by estimating the future returns of the stocks is found to perform sub-optimally on real-world stock market data. This is because the estimation task becomes extremely challenging due to the stochastic and volatile nature of stock prices. This work illustrates three approaches to portfolio design minimising the risk, optimising the risk, and assigning equal weights to the stocks of a portfolio. Thirteen critical sectors listed on the National Stock Exchange (NSE) of India are first chosen. Three portfolios are designed following the above approaches choosing the top ten stocks from each sector based on their free-float market capitalisation. The portfolios are designed using the historical prices of the stocks from 1 January 2017 to 31 December 2022. The portfolios are evaluated on the stock price data from 1 January 2022 to 31 December 2022. The performances of the portfolios are compared, and the portfolio yielding the higher return for each sector is identified.

Keywords: return; risk; minimum risk portfolio; MRP; mean-variance portfolio; optimum risk portfolio; ORP; Sharpe ratio.

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1 Introduction

Portfolio optimisation is the process of identification of a set of capital assets and their respective weights allocation such that the risk-return pairs are optimised. The optimisation problem is further confounded due to the requirement of the estimation of the future returns of stocks that exhibit volatility in their prices. Quite a few experts on the *efficient market hypothesis* (Fama, 1998, 1970; Fama and French, 1998, 1993) believe that accurate forecasting of future stock prices is not possible. Numerous propositions in the literature, however, illustrate the effective usage of complex algorithms and the design of predictive models to precisely predict future stock prices. Several propositions have been made on various portfolio optimisation approaches following Markowitz's (1952) seminal work on minimum-variance portfolios. Several statistical and econometric, and learning-based approaches for future stock price prediction based on methods such as *multivariate regression*, *autoregressive integrated moving average* (*ARIMA*), *vector autoregression* (*VAR*), time series forecasting, machine learning, and deep learning, have also been proposed in the literature.

This paper presents a methodical approach to building robust stock portfolios in 13 key sectors of the Indian economy. For each of these 13 sectors, the top ten stocks based on their free-float market capitalisation in the National Stock Exchange (NSE) are identified (NSE Website, 2023). The ticker names of these 130 stocks are used to automatically scrape their historical prices from the Yahoo Finance Website (2023). Using these historical prices over five years, three different portfolios are designed following the equal weight allocation, minimum risk portfolio (MRP) allocation, and mean-variance portfolio allocation. In the rest of the chapter, the mean-variance portfolio is referred to as the optimum risk portfolio (ORP). The portfolio performances are evaluated based on their annual returns over the year 2022. Moreover, other characteristics of the portfolios such as risk, weights assigned to constituent stocks, and the correlation among the stocks, are also analysed. The study elucidates a comparative understanding of portfolio performances, along with actual return and volatility for the 13 sectors. As an immediate use of this work, stock market investors can exploit the results of this work to gain comprehensive information on the current return on investment (ROI), and the risk involved in the sectors and the stocks analysed in this work.

The work has three major contributions. First, this work presents two approaches toward stock portfolio design, the equal-weight portfolio, and the mean-variance portfolio. These two portfolio design approaches are used to build sectoral portfolios of stocks from 13 important sectors listed in the NSE, India. The performance results of these portfolios will be a good indicator of the current profitability of these sectors, and hence, the results will be a good guide for investors of the Indian stock market. Second, the results of this work will enable one to understand the potential return and the risk associated with the stocks of the 13 sectors analysed in this study. Third, the study also reveals which portfolio design approach yields a higher return and a lower risk for a given sector.

The paper is organised as follows. Section 2 presents a summary of some of the important related works. Section 3 describes the data and methodology pursued in the design of portfolios. Section 4 provides extensive results on portfolio performances, along with a detailed analysis of the same. Finally, the paper is concluded in Section 5, in which some future directions of work are highlighted.

2 Related work

Portfolio design and optimisation is a challenging problem for which numerous solutions and approaches have been proposed by researchers. Portfolio design and optimisation is a challenging problem that has attracted considerable attention from researchers. Numerous approaches have been proposed to solve this complex problem involving robust stock price prediction and the formation of the optimised combination of stocks to maximise the ROI. Machine learning models have been extensively used by researchers in predicting future stock prices (Carta et al., 2021; Chatterjee et al., 2021; Mehtab and Sen, 2021, 2020a, 2019; Mehtab et al., 2021; Sarmento and Horta, 2020; Sen, 2018a; Sen and Datta Chaudhuri, 2017a). The prediction accuracies of the models are found to have been improved by the use of deep learning architectures and algorithms (Chatterjee et al., 2021; Chen et al., 2018; Chong et al., 2017; Mehtab and Sen, 2022, 2021, 2020a, 2020b, 2019; Mehtab et al., 2021, 2020; Sen, 2018a; Sen and Mehtab, 2021a, 2021b; Sen et al., 2021a, 2021b, 2021i, 2020; Thormann et al., 2021; Tran et al., 2019). Several approaches to text mining have been effectively applied on social media and the web to improve prediction accuracies even further (Li and Pan, 2022; Mehtab and Sen, 2019; Thormann et al., 2021; Zhang et al., 2021). Among the other alternative approaches for stock price prediction, time series decomposition-based statistical and econometric approaches are also quite popular (Chatterjee et al., 2021; Cheng et al., 2018; Sen, 2022a, 2018b, 2017a, 2017b; Sen and Datta Chaudhuri, 2018, 2017b, 2017c, 2016a, 2016b, 2016c, 2016d, 2015). For estimating the future volatility and risk of stock portfolios the use of several variants of GARCH has been proposed in some works (Sen et al., 2021d). Over the last few years, reinforcement learning has been extensively used in robust and accurate prediction of stock prices and portfolio design (Brim, 2020; Fengqian and Chao, 2020; Kim et al., 2022; Kim and Kim, 2019; Lei et al., 2020; Li et al., 2019; Lu et al., 2021; Park and Lee, 2021).

The classical mean-variance optimisation approach is the most well-known method for portfolio optimisation (Sen and Mehtab, 2022, 2021b; Sen et al., 2021e, 2021g, 2021h). Several alternatives to the mean-variance approach to portfolio optimisation have also been proposed by some researchers. Notable among these methods are multi-objective optimisation (Wang et al., 2022; Zheng and Zheng, 2022), Eigen portfolios using principal component analysis (Sen and Dutta, 2022a; Sen and Mehtab, 2022), risk parity-based methods (Sen and Dutta, 2022a, 2021; Sen et al., 2021c, 2021f), and swarm intelligence-based approaches (Corazza et al., 2021; Thakkar and Chaudhuri, 2021). The use of genetic algorithms (Kaucic et al., 2019), fuzzy sets (Karimi et al., 2022), prospect theory (Li et al., 2021), and quantum evolutionary algorithms (Chou et al., 2021), cointegration-based approaches (Sen, 2022b, 2022c; Flori and Ragoli, 2021; Gupta and Chatterjee, 2020; Ramos-Requena et al., 2021) are also proposed in the literature.

In the present work, the design of portfolios of stocks in 13 key sectors of the Indian stock market is done following three portfolio-building methodologies, viz., equal weight portfolio (EWP), MRP, and ORP. The portfolios for each of these sectors are designed using the historical prices of the top ten stocks in NSE over five years (i.e., from 1 January 2017 to 31 December 2021). For each sector, the performances of the equal-weight portfolio and the mean-variance portfolio are evaluated based on their annual returns over the test period from 1 January 2022 to 31 December 2022, and the portfolio yielding the higher return is identified.

3 Data and methodology

This section presents a detailed discussion of the steps involved in the data acquisition, data pre-processing, and the design of the portfolios for the 13 sectors of stocks listed in the NSE. The process consists of seven steps which are as follows.

3.1 The selection of the sectors

As discussed in Section 1, 13 sectors are selected from the NSE, India. The sectors are *auto*, *banking*, *consumer durables*, *financial services*, *fast-moving consumer goods* (*FMCG*), *information technology* (*IT*), *media*, *metal*, *oil and gas*, *pharma*, *public sector banks*, *private banks*, and *realty*. Based on the free-float market capitalisation in the NSE, the top ten stocks for each of the above-mentioned sectors are identified. The sector-specific portfolios are built using those stocks.

3.2 Data acquisition

For each sector, the prices of the stocks are acquired from the Yahoo Finance site using the *YahooFinancials* function. The parameters passed in the function are the *ticker name*, and the *date range* from 1 January 2017 to 31 December 2022, with ‘daily’ frequency. The extracted stock data have the following attributes:

1 open

2 high

3 close

4 volume

5 adjusted close.

This work is based on univariate analysis and hence the variable ‘close’ is chosen as the variable of interest, while the remaining variables are ignored. The close values of the ten stocks, from 1 January 2017 to 31 December 2021, are used for building the portfolios. The portfolios are tested for their returns from 1 January 2022 to 30 December 2022.

3.3 Deriving the stock returns and volatility

The *daily return*, which is the percentage change in consecutive daily *close* prices, for each stock is computed on the training data using the *pct_change* function of Python. The annual return for each stock is computed as the weighted sum of the daily returns for the stock. Using the daily return values, the daily and annual volatility of the stocks are then calculated, using equations (1) and (2) ions.

$$\textit{Daily volatility}\ (D_v) = \textit{standard deviation of daily returns} \tag{1}$$

$$\begin{aligned}&\textit{Annual volatility}\\&= D_v \times \sqrt{250}, \textit{ assuming } 250 \textit{ working days/year for stock market}\end{aligned} \tag{2}$$

Since annual volatility indicates price variability, it provides investors with a measure of the risk associated with a stock. The *std* function of Python function is used to calculate the volatility of stocks.

3.4 The covariance and correlation matrices computation

In the next step, to get an understanding of the association strength between the close prices of a pair of stocks in a sector, their covariance and correlation matrices are calculated using the training dataset. A strong association of a pair is indicated by a high covariance value between them and vice-versa. The matrices are computed using the *cov* and *corr* Python functions. A good portfolio aims to optimise the return while minimising its risk. To minimise the risk, the identification of stocks with low correlation among them is required. This helps in achieving a higher diversity in the portfolio, thereby reducing its risk.

3.5 The design of equal-weight portfolios

Now we delve deep into historical price analysis of the chosen stocks in each sector. Using equal weights of the stocks, sector-wise portfolios are created. As we are working with ten stocks per sector, the weight assigned to every stock is 0.1. The yearly returns, along with associated risks, are calculated based on the training data assuming equal weight allocation to the stocks. The expected return of a portfolio is computed using equation (3) in which, $E(R)$ denotes the expected return of an n-stock portfolio where each stock is denoted as S_1, S_2, …, S_n. The associated weights of the stocks are represented by w_i’s.

$$E(R) = w_1 E(R_{S_1}) + w_2 E(R_{S_2}) + \ldots + w_n E(R_{S_n}) \tag{3}$$

For calculating the equal weights portfolios of each sector, the *resample* function of Python is used with the parameter set to '*Y*' so that the yearly mean values are computed.

3.6 The design of the MRPs

Similar to the EWPs, the MRPs are designed for all sectors. A portfolio with the minimum variance is identified as the MRP. The variance of a portfolio is calculated using variances of every stock and covariances between each stock-pair in it, as shown in equation (4).

$$Var(P) = \sum_{i=1}^{n} w_i \sigma_i^2 + 2\sum_{i,j} w_i w_j Cov(i, j) \tag{4}$$

Since ten stocks of each sector are used in this work, the variance computation involves 55 terms per portfolio, where the weighted variances contribute ten terms and the weighted covariances contribute the remaining 45. To build the MRPs, we find the weight combination that minimises the portfolio variance. For each portfolio, first, the efficient frontier is plotted. The efficient frontier is the contour of the portfolios that indicates portfolios with the maximum returns for a given risk (Sen and Mehtab, 2022). The leftmost point on the efficient frontier indicates the portfolio with minimum risk. For plotting the effective frontier, 10,000 portfolios are designed with random weights allocation to the 10 constituent stocks using a for loop in a Python program. Each of these 10,000 portfolios is represented as a point in two-dimensional space, constituting the efficient frontier. That point on the efficient frontier, which is at the leftmost position, is used as a minimum-risk portfolio.

3.7 The design of the ORP

Investors are normally not interested in the low return values yielded by the MRP. Generally, they have the appetite to take some risks, provided the returns are high. A metric known as the Sharpe ratio is used to trade-off portfolio return and risk. The Sharpe ratio of a portfolio is defined as the ratio of the return yielded by the portfolio to the return of a risk-free portfolio (Sen and Dutta, 2022b). This ratio is used to identify the portfolio with the optimum risk. In computing the Sharpe ratio, the volatility of the risk-free portfolio is assumed to be 1%. By maximising the Sharpe ratio for the constituent stocks, the ORP trades off the risk with the return, thereby making the return significantly higher. The *idmax* function of Python has been used to find the portfolio with the highest Sharpe ratio (i.e., the ORP) among all points of an effective frontier.

4 Experimental results

In this section, the details of the portfolio design, their performance results, and an extensive analysis of the results are presented. Python 3.7.4 and its libraries have been used to implement the portfolio models, while training and testing of the models have been done using Jupyter Notebook. A work station running on the Windows 11 operating system, an Intel i5-9300H CPU with a clock speed of 2.40 GHz, and a RAM of 8 GB have been used for training and testing of the portfolios. The results and analysis for each sector are presented separately as follows.

4.1 The auto sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 1 and 2 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the auto sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 Mahindra & Mahindra (M&M): 20.08.

2 Maruti Suzuki India (MARUTI):18.74.

3 Tata Motors (TATAMOTORS): 11.69.

4 Eicher Motors (EICHERMOT): 7.56.

5 Bajaj Auto (BAJAJ-AUTO): 6.87.

6 Hero MotoCorp (HEROMOTOCO): 5.97.

7 Tube Investments of India (TIINDIA): 4.86.

8 TVS Motor Company (TVSMOTOR): 4.24.

9 Bharat Forge (BHARATFORG): 3.78.

10 Ashok Leyland (ASHOKLEY): 3.46.

Table 1 represents the annual return and volatility for auto-sector stocks for the training period from 1 January 2017 to 31 December 2021. TIINDIA shows the highest annual return while MARUTI yields the lowest. TATAMOTORS has the highest annual risk while BAJAJ-AUTO has the lowest.

Table 1 The return and risk of the auto sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
M&M	6.22	32.68
MARUTI	–5.92	30.89
TATAMOTORS	27.22	47.92
EICHERMOT	–2.91	33.53
BAJAJ-AUTO	0.29	26.38
HEROMOTOCO	–8.21	29.98
TIINDIA	63.19	39.29
TVSMOTOR	–2.77	33.86
BHARATFORG	1.52	38.17
ASHOKLEY	2.74	45.06

Table 2 presents the weights allocation to different stocks, using three portfolio design approaches:

1 EWP

2 MRP

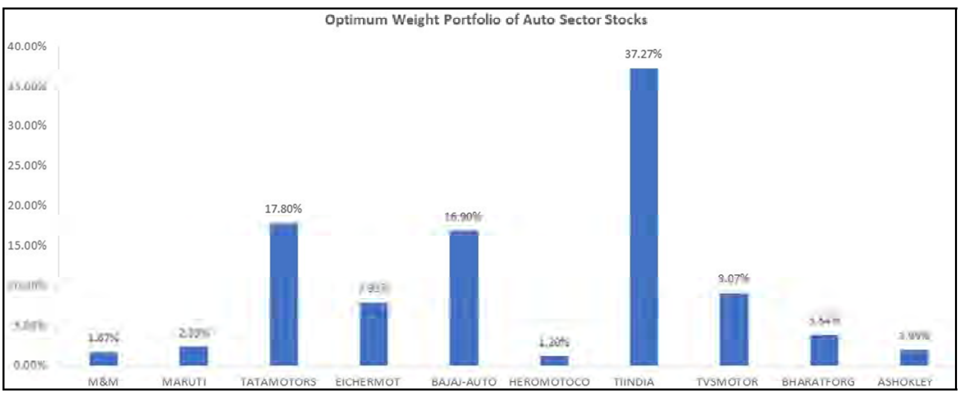
3 MVP/ORP.

In each of the above cases, the sum of weights is 1.

Table 2 The portfolio weights for the auto sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
M&M	0.1	0.064107	0.016697
MARUTI	0.1	0.163289	0.023862
TATAMOTORS	0.1	0.028795	0.178039
EICHERMOT	0.1	0.122902	0.079096
BAJAJ-AUTO	0.1	0.242138	0.169046
HEROMOTOCO	0.1	0.072284	0.011963
TIINDIA	0.1	0.155767	0.372677
TVSMOTOR	0.1	0.149395	0.090742
BHARATFORG	0.1	0.000088	0.038361
ASHOKLEY	0.1	0.001234	0.019517

Figure 1 The ORP portfolio weights for the auto sector stocks (see online version for colours)



BAJAJ-AUTO receives the highest allocation as per the MRP while TIINDIA receives the highest allocation as per the ORP.

Figure 1 depicts the weight allocation to the auto sector stocks done by the ORP.

Table 3 The return and risk of the auto sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	8.14	8.77	27.94
Portfolio annual risk (%)	24.46	22.45	25.60

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 3. It is evident that the equal weights portfolio has yielded the lowest return and the MRP has exhibited the least risk. The ORP has produced the highest return and the highest risk. It should be noted that since the MRP yields a very low return, it is not adopted by investors. Hence, its performance is not evaluated over the test data for all sectors.

Table 4 The return of the equal-weight portfolio of the auto sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price/ stock*	*Amount invested*	*No. of stock*	*Price/ stock*	*Value of stock*	
M&M	0.1	830	10,000	12.05	1,249	15,054	23.52%
MARUTI	0.1	7,524	10,000	1.33	8,395	11,157	
TATAMOTORS	0.1	498	10,000	20.1	388	7,796	
EICHERMOT	0.1	2,719	10,000	3.68	3,228	11,872	
BAJAJ-AUTO	0.1	3,277	10,000	3.05	3,616	11,034	
HEROMOTOCO	0.1	2,477	10,000	4.04	2,739	11,059	
TIINDIA	0.1	1,889	10,000	5.29	2,776	14,696	
TVSMOTOR	0.1	629	10,000	15.89	1,085	17,249	
BHARATFORG	0.1	711	10,000	14.07	880	12,377	
ASHOKLEY	0.1	128	10,000	78.31	143	11,229	
			100,000			123,523	

The annual return for an investor, investing INR100,000 on 3 January 2022, and following the EWP approach is shown in Table 4. The investor receives a return of 23.52% at the end of the 12 months.

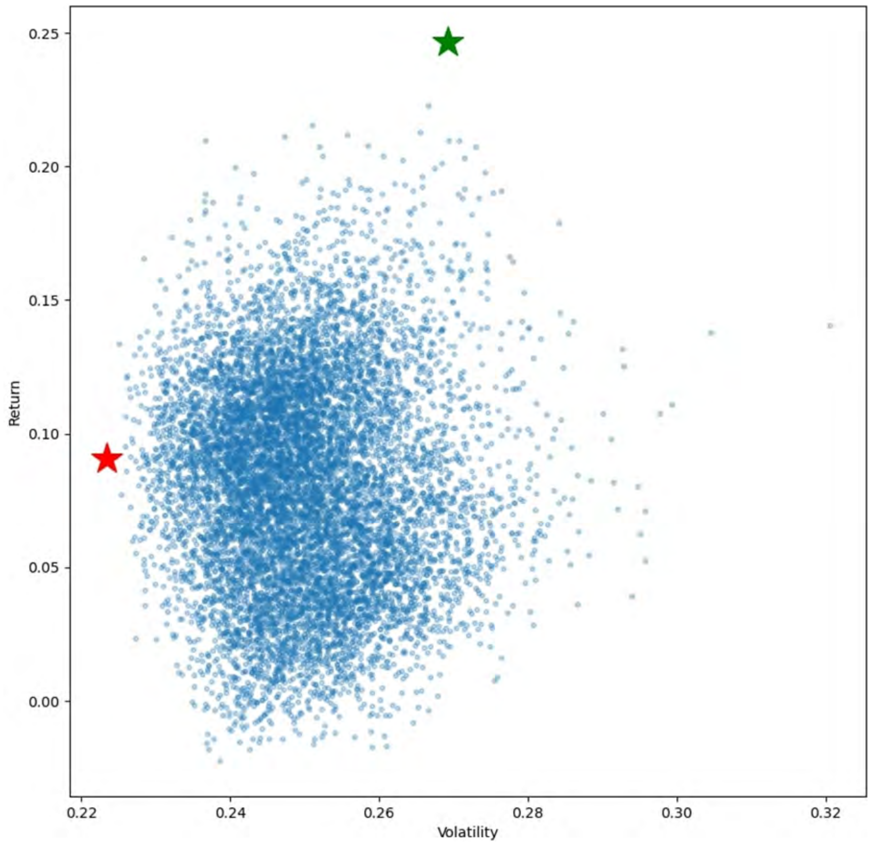
The performance of the ORP for the auto-sector stocks is shown in Table 5. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be 25.78% as depicted in Table 5.

Table 5 The return of the ORP of the auto sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
M&M	0.016697	830	1,670	2.01	1,249	2,514	25.78%
MARUTI	0.023862	7,524	2,386	0.32	8,395	2,662	
TATAMOTORS	0.178039	498	17,804	35.78	388	13,881	
EICHERMOT	0.079096	2,719	7,910	2.91	3,228	9,390	
BAJAJ-AUTO	0.169046	3,277	16,905	5.16	3,616	18,653	
HEROMOTOCO	0.011963	2,477	1,196	0.48	2,739	1,323	
TIINDIA	0.372677	1,889	37,268	19.73	2,776	54,770	
TVSMOTOR	0.090742	629	9,074	14.42	1,085	15,652	
BHARATFORG	0.038361	711	3,836	5.4	880	4,748	
ASHOKLEY	0.019517	128	1,952	15.28	143	2,192	
			100,000			125,785	

Finally, the efficient frontier for the auto sector portfolios is presented in Figure 2. In Figure 2, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the auto sector. It is to be noted that in Figure 2, the x-axis denotes the risk while the y-axis denotes the return.

Figure 2 The efficient frontier of the auto sector portfolios (see online version for colours)



4.2 The banking sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 3 and 4 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the banking sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 HDFC Bank (HDFCBANK): 28.66.

2 ICICI Bank (ICICIBANK):23.54.

3 Kotak Mahindra Bank (KOTAKBANK): 10.18.

4 Axis Bank (AXISBANK): 10.01.

5 State Bank of India (SBIN): 9.85.

6 IndusInd Bank (INDUSINDBK): 5.91.

7 Bank of Baroda (BANKBARODA): 2.62.

8 AU Small Finance Bank (AUBANK): 2.49.

9 Federal Bank (FEDERALBANK): 2.38

10 IDFC First Bank (IDFCFIRSTB): 1.55.

Table 6 represents the annual return and volatility for banking sector stocks for the training period from 1 January 2017 to 31 December 2021. ICICIBANK produces the highest annual return while INDUSINDBK yields the lowest return. INDUSINDBK also has the highest annual risk while HDFCBANK has the lowest.

Table 6 The return and risk of the banking sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
HDFCBANK	12.28	24.91
ICICIBANK	25.49	35.63
AXISBANK	5.80	38.54
SBIN	14.53	36.87
KOTAKBANK	16.73	29.28
INDUSINDBK	–12.52	48.43
BANKBARODA	–11.65	45.39
AUBANK	12.53	43.05
FEDERALBNK	–4.87	40.64
IDFCFIRSTB	–0.85	41.21

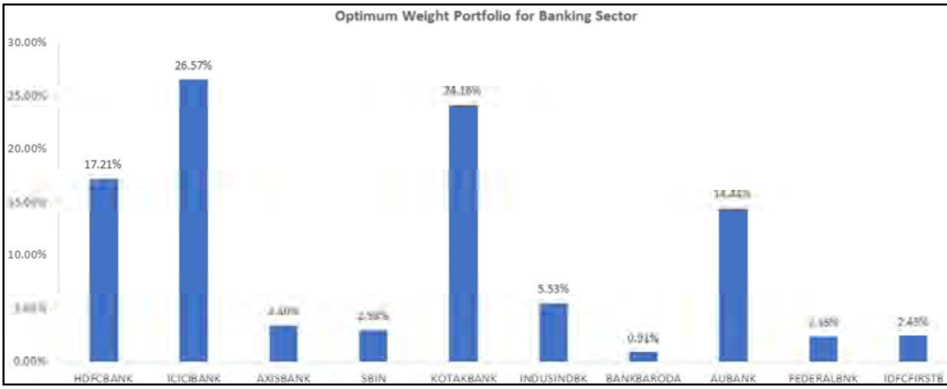
Table 7 presents the weights allocation to different stocks for the three portfolio design approaches. HDFCBANK receives the highest allocation as per the MRP while ICICIBANK receives the highest allocation as per the ORP.

Table 7 The portfolio weights for the banking sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
HDFCBANK	0.1	0.295298	0.058031
ICICIBANK	0.1	0.101177	0.233981
AXISBANK	0.1	0.003179	0.103966
SBIN	0.1	0.070569	0.173993
KOTAKBANK	0.1	0.219924	0.175173
INDUSINDBK	0.1	0.048226	0.018862
BANKBARODA	0.1	0.039036	0.002539
AUBANK	0.1	0.095645	0.196626
FEDERALBNK	0.1	0.079754	0.024523
IDFCFIRSTB	0.1	0.047192	0.012306

Figure 3 depicts the weight allocation to the banking sector stocks done by the ORP.

Figure 3 The ORP portfolio weights for the banking sector stocks (see online version for colours)



The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 8. It is evident that the EWP has yielded the lowest return and the MRP has exhibited the least risk. The ORP has produced the highest return, while the EWP has exhibited the highest risk.

Table 8 The return and risk of the banking sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	5.75%	10.64%	14.81%
Portfolio annual risk (%)	27.45%	24.21%	26.67%

The annual return for an investor, investing INR100,000 on 3 January 2022, and following the EWP approach is shown in Table 9. The investor receives a return of 34.43% at the end of the 12 months.

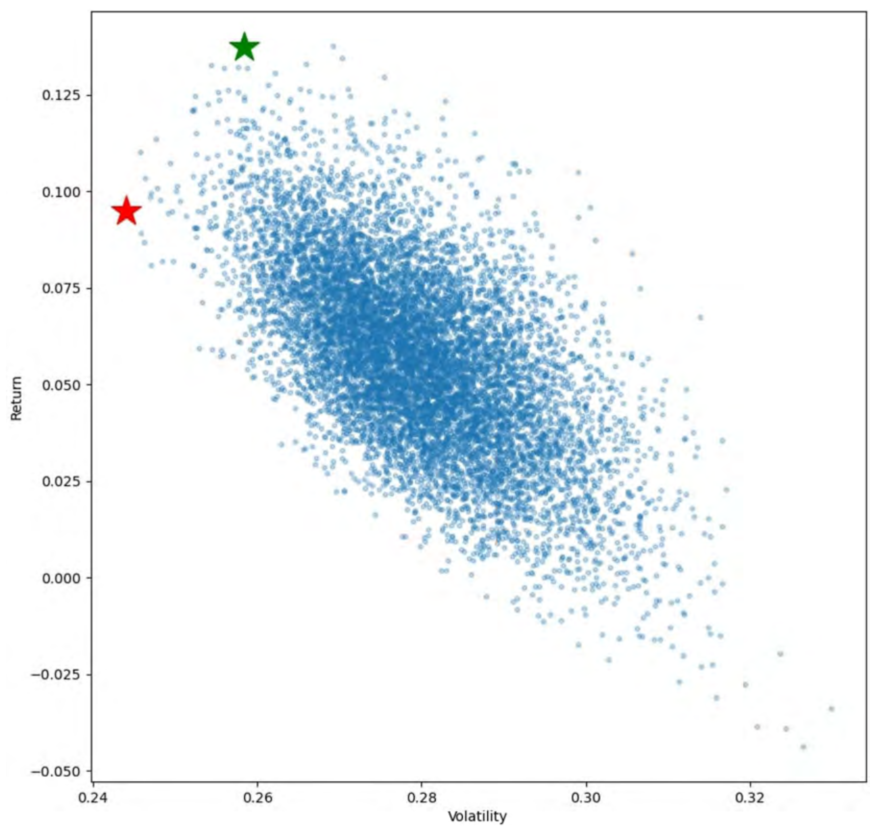
Table 9 The return of the equal-weight portfolio of the banking sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
HDFCBANK	0.1	1,520	10,000	6.58	1,628	10,714	34.43%
ICICIBANK	0.1	765	10,000	13.08	891	11,650	
AXISBANK	0.1	696	10,000	14.36	934	13,409	
SBIN	0.1	471	10,000	21.24	614	13,035	
KOTAKBANK	0.1	1,824	10,000	5.48	1,827	10,015	
INDUSINDBK	0.1	912	10,000	10.96	1,220	13,374	
BANKBARODA	0.1	84	10,000	119.33	186	22,160	
AUBANK	0.1	533	10,000	18.77	654	12,287	
FEDERALBNK	0.1	87	10,000	114.68	139	15,946	
IDFCFIRSTB	0.1	50	10,000	201.41	59	11,843	
			100,000			134,433	

Table 10 The return of the ORP of the banking sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
HDFCBANK	0.058031	1,520	5,803	3.82	1,628	6,217	20.25%
ICICIBANK	0.233981	765	23,398	30.6	891	27,258	
AXISBANK	0.103966	696	10,397	14.93	934	13,941	
SBIN	0.173993	471	17,399	36.96	614	22,680	
KOTAKBANK	0.175173	1,824	17,517	9.6	1,827	17,544	
INDUSINDBK	0.018862	912	1,886	2.07	1,220	2,523	
BANKBARODA	0.002539	84	254	3.03	186	563	
AUBANK	0.196626	533	19,663	36.91	654	24,159	
FEDERALBNK	0.024523	87	2,452	28.12	139	3,910	
IDFCFIRSTB	0.012306	50	1,231	24.79	59	1,457	
			100,000			120,252	

Figure 4 The efficient frontier of the banking sector portfolios (see online version for colours)



The performance of the ORP for the banking-sector stocks is shown in Table 10. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be 20.25% as depicted in Table 10.

Finally, the efficient frontier for the banking sector portfolios is presented in Figure 4. In Figure 4, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the banking sector. It is to be noted that in Figure 4, the x-axis denotes the risk while the y-axis denotes the return.

4.3 The consumer durables sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 5 and 6 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the consumer durables sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1. Titan Company (TITAN): 32.31.
2. Havells India (HAVELLS): 14.31.
3. Crompton Greaves Consumer Electricals (CROMPTON): 9.87.
4. Voltas (VOLTAS): 8.99.
5. Rajesh Exports (RAJESHEXPO): 5.61.
6. Dixon Technologies (DIXON): 4.79.
7. Bata India (BATAINDIA): 4.75.
8. Kajaria Ceramics (KAJARIACER): 4.30.
9. Blue Star (BLUESTARCO): 3.43.
10. Relaxo Footwears (RELAXO): 2.86.

Table 11 represents the annual return and volatility for the consumer durables sector stocks for the training period from 1 January 2017 to 31 December 2021. DIXON shows the highest annual return and the highest risk, while RAJESHEXPO yields the lowest return and the lowest risk.

Table 12 presents the weights allocation to different stocks for the three portfolio design approaches. RAJESHEXPO receives the highest allocation as per the MRP while DIXON receives the highest allocation as per the ORP.

Figure 5 depicts the weight allocation to the consumer durables sector stocks done by the ORP.

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 13. It is evident that the ORP yields the highest return and it also exhibits the highest risk.

Table 11 The return and risk of the consumer durables sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
TITAN	32.24	33.44
HAVELLS	27.65	31.49
CROMPTON	15.39	32.40
VOLTAS	19.10	31.28
DIXON	98.05	40.36
BATAINDIA	28.72	29.30
RAJESHEXPO	2.97	27.50
KAJARIACER	22.86	32.44
BLUESTARCO	8.18	31.61
RELAXO	42.47	29.45

Table 12 The portfolio weights for the consumer durables sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
TITAN	0.1	0.110719	0.067351
HAVELLS	0.1	0.069098	0.06275
CROMPTON	0.1	0.121852	0.033558
VOLTAS	0.1	0.011657	0.031573
DIXON	0.1	0.023866	0.329759
BATAINDIA	0.1	0.036811	0.151651
RAJESHEXPO	0.1	0.369238	0.130582
KAJARIACER	0.1	0.010017	0.012794
BLUESTARCO	0.1	0.100789	0.026107
RELAXO	0.1	0.145953	0.153873

Figure 5 The ORP portfolio weights for the consumer durables sector stocks (see online version for colours)

Table 13 The return and risk of the consumer durables sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	29.76	19.32	49.14
Portfolio annual risk (%)	18.05	17.01	20.79

Table 14 The return of the equal-weight portfolio of the consumer durables sector stocks

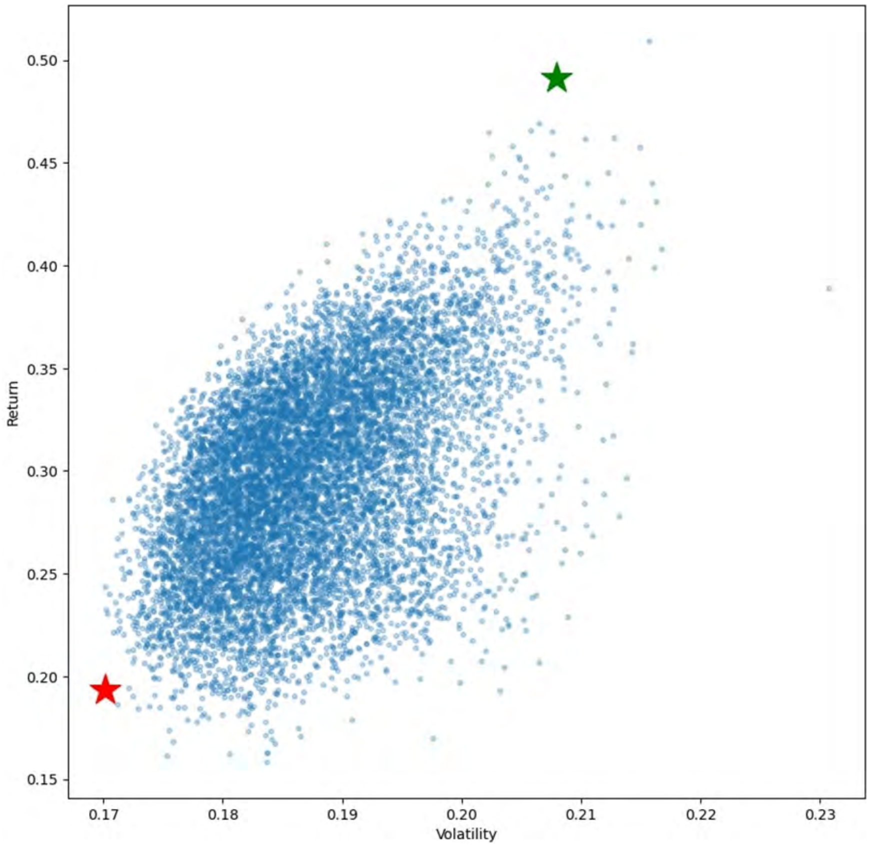
Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
TITAN	0.1	2,524	10,000	3.96	2,598	10,286	–15.74%
HAVELLS	0.1	1,406	10,000	7.11	1,100	7,821	
CROMPTON	0.1	441	10,000	22.65	336	7,621	
VOLTAS	0.1	1,233	10,000	8.11	800	6,487	
DIXON	0.1	5,517	10,000	1.81	3,905	7,067	
BATAINDIA	0.1	1,859	10,000	5.38	1,649	8,872	
RAJESHEXPO	0.1	853	10,000	11.73	732	8,583	
KAJARIACER	0.1	1,315	10,000	7.6	1,160	8,818	
BLUESTARCO	0.1	1,015	10,000	9.85	1,200	11,816	
RELAXO	0.1	1,321	10,000	7.57	910	6,889	
			100,000			84,260	

The return of the equal-weight portfolio of the consumer durables sector stocks for an investor, investing INR100,000 on 3 January 2022, is shown in Table 14. The investor receives a return of –15.74% at the end of the 12 months. The negative sign indicates that the investor has suffered a loss when using the equal-weight portfolio.

Table 15 The return of the ORP of the consumer durables sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
TITAN	0.067351	2,524	6,735	2.67	2,598	6,932	–20.74%
HAVELLS	0.06275	1,406	6,275	4.46	1,100	4,909	
CROMPTON	0.033558	441	3,356	7.6	336	2,558	
VOLTAS	0.031573	1,233	3,157	2.56	800	2,048	
DIXON	0.329759	5,517	32,976	5.98	3,905	23,338	
BATAINDIA	0.151651	1,859	15,165	8.16	1,649	13,452	
RAJESHEXPO	0.130582	853	13,058	15.32	732	11,207	
KAJARIACER	0.012794	1,315	1,280	0.97	1,160	1,129	
BLUESTARCO	0.026107	1,015	2,611	2.57	1,200	3,084	
RELAXO	0.153873	1,321	15,387	11.65	910	10,599	
			100,000			79,256	

Figure 6 The efficient frontier of the consumer durables sector portfolios (see online version for colours)



The performance of the ORP for the consumer durables sector stocks is shown in Table 15. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be –20.74% indicating a loss for the investor.

Finally, the efficient frontier for the consumer durables sector portfolios is presented in Figure 6. In Figure 6, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the consumer durables sector. It is to be noted that in Figure 6, the x-axis denotes the risk while the y-axis denotes the return.

4.4 The FMCG sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 7 and 8 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the FMCG sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 ITC (ITC): 32.39.
2 Hindustan Unilever (HINDUNILVR): 24.00.
3 Nestle India (NESTLEIND): 7.08.
4 Britannia Industries (BRITANNIA): 6.23.
5 Tata Consumer Products (TATACONSUM): 5.39.
6 Godrej Consumer Products (GODREJCP): 4.23.
7 Dabur India (DABUR): 3.87.
8 Varun Beverages (VBL): 3.28.
9 Marico (MARICO): 3.15.
10 United Spirits (MCDOWELL-N): 2.80.

Table 16 represents the annual return and volatility for the FMCG sector stocks for the training period from 1 January 2017 to 31 December 2021. VBL produces the highest annual return while ITC yields the lowest return. VBL also has the highest annual risk while HINDUNILVR has the lowest.

Table 17 presents the weights allocation to different stocks for the three portfolio design approaches. ITC receives the highest allocation as per the MRP while TATACONSUM receives the highest allocation as per the ORP.

Figure 7 depicts the weight allocation to the FMCG sector stocks done by the ORP.

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 18. It is evident that the ORP yields the highest return and it also exhibits the highest risk.

The annual return for an investor, investing INR100,000 on 3 January 2022, and following the EWP approach is shown in Table 19. The investor receives a return of 19.10% at the end of the 12 months.

Table 16 The return and risk of the FMCG sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
ITC	–4.09	27.58
HINDUNILVR	15.45	23.05
NESTLEIND	26.44	23.76
BRITANNIA	12.11	24.73
TATACONSUM	31.35	33.79
DABUR	13.68	23.57
GODREJCP	11.27	30.68
VBL	32.58	34.96
MCDOWELL-N	8.18	34.06
MARICO	13.11	24.07

The performance of the ORP for the FMCG sector stocks is shown in Table 20. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be 30.29% as depicted in Table 20.

Table 17 The portfolio weights for the FMCG sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
ITC	0.1	0.164083	0.02965
HINDUNILVR	0.1	0.103406	0.059826
NESTLEIND	0.1	0.153909	0.214773
BRITANNIA	0.1	0.132328	0.043768
TATACONSUM	0.1	0.001555	0.228231
DABUR	0.1	0.102624	0.016151
GODREJCP	0.1	0.069028	0.032177
VBL	0.1	0.121421	0.219175
MCDOWELL-N	0.1	0.012792	0.064606
MARICO	0.1	0.138854	0.091642

Figure 7 The ORP portfolio weights for the FMCG sector stocks (see online version for colours)

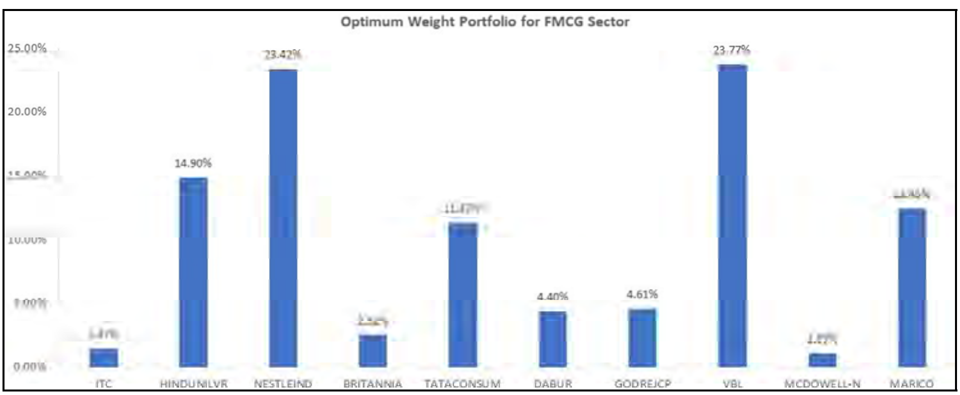


Table 18 The return and risk of the FMCG sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	16.01	14.71	23.62
Portfolio annual risk (%)	16.57	15.84	18.13

Finally, the efficient frontier for the FMCG sector portfolios is presented in Figure 8. In Figure 8, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the FMCG sector. It is to be noted that in Figure 8, the x-axis denotes the risk while the y-axis denotes the return.

Table 19 The return of the equal-weight portfolio of the FMCG sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
ITC	0.1	219	10,000	45.64	332	15,132	19.10%
HINDUNILVR	0.1	2,361	10,000	4.23	2,561	10,846	
NESTLEIND	0.1	19,678	10,000	0.51	19,606	9,963	
BRITANNIA	0.1	3,618	10,000	2.76	4,307	11,907	
TATACONSUM	0.1	748	10,000	13.37	767	10,253	
DABUR	0.1	581	10,000	17.21	561	9,661	
GODREJCP	0.1	958	10,000	10.44	874	9,128	
VBL	0.1	587	10,000	17.05	1,323	22,549	
MCDOWELL-N	0.1	901	10,000	11.1	878	9,744	
MARICO	0.1	514	10,000	19.45	510	9,917	
			100,000			119,100	

Figure 8 The efficient frontier of the FMCG sector portfolio (see online version for colours)

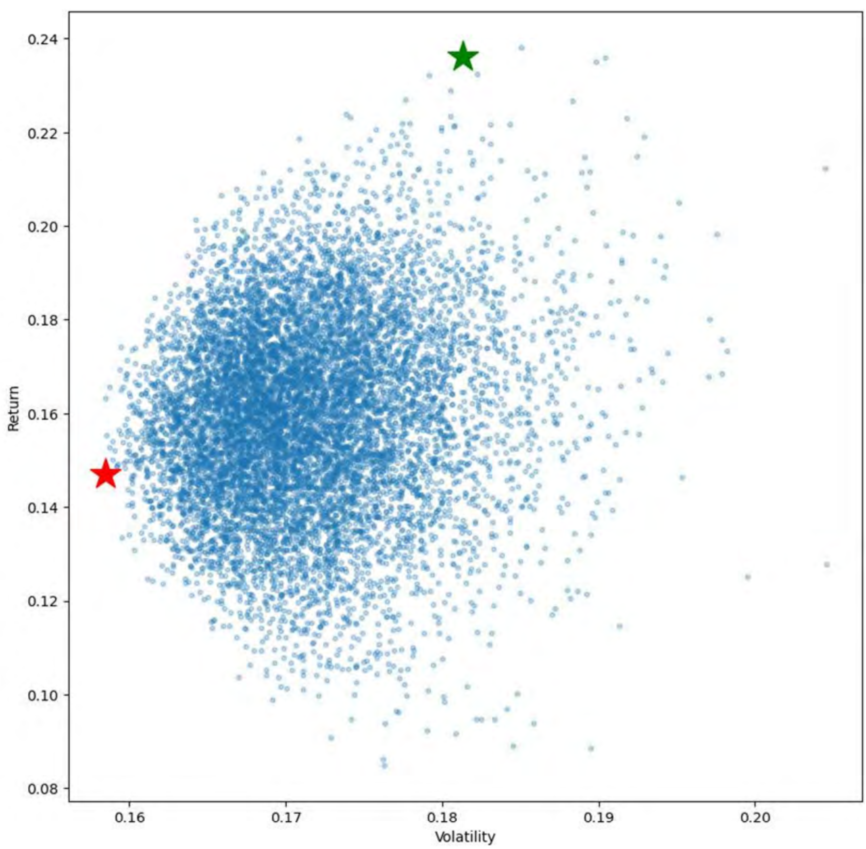


Table 20 The return of the ORP of the FMCG sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
ITC	0.02965	219	2,965	13.53	332	4,487	30.29%
HINDUNILVR	0.059826	2,361	5,983	2.53	2,561	6,489	
NESTLEIND	0.214773	19,678	21,477	1.09	19,606	21,399	
BRITANNIA	0.043768	3,618	43,77	1.21	4,307	5211	
TATACONSUM	0.228231	748	22,823	30.51	767	23,401	
DABUR	0.016151	581	1,615	2.78	561	1,560	
GODREJCP	0.032177	958	3,218	Auto 3.36	874	2,937	
VBL	0.219175	587	21,918	37.37	1,323	49,421	
MCDOWELL-N	0.064606	901	6,460	7.17	878	6,295	
MARICO	0.091642	514	9,164	17.83	510	9,088	
			100,000			130,288	

4.5 The financial services sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 9 and 10 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the financial services sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 HDFC Bank (HDFCBANK): 23.62.

2 ICICI Bank (ICICIBANK): 19.41.

3 Housing Development Finance Corporation (HDFC): 15.82.

4 Kotak Mahindra Bank (KOTAKBANK): 8.39.

5 Axis Bank (AXISBANK): 7.89.

6 State Bank of India (SBIN): 7.10.

7 Bajaj Finance (BAJFINANCE): 5.24.

8 Bajaj Finserv (BAJAJFINSV): 2.43.

9 HDFC Life Insurance Company (HDFCLIFE): 1.91.

10 SBI Life Insurance Company (SBILIFE): 1.84.

Table 21 represents the annual return and volatility for the financial services sector stocks for the training period from 1 January 2017 to 31 December 2021. BAJAJFINANCE shows the highest annual return while AXISBANK yields the lowest. BAJAJFINANCE also has the highest annual risk while HDFCBANK has the lowest.

Table 21 The return and risk of the financial services sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
HDFCBANK	12.28	24.91
ICICIBANK	25.49	35.63
HDFC	11.20	30.27
KOTAKBANK	16.73	29.28
AXISBANK	5.80	38.54
SBIN	14.53	36.87
BAJFINANCE	41.87	40.69
BAJAJFINSV	36.97	37.23
SBILIFE	18.28	30.20
HDFCLIFE	16.52	32.64

Table 22 presents the weights allocation to different stocks for the three portfolio design approaches. SBILIFE receives the highest allocation as per the MRP while BAJAJFINANCE receives the highest allocation as per the ORP.

Table 22 The portfolio weights for the financial services sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
HDFCBANK	0.1	0.226283	0.091791
ICICIBANK	0.1	0.000271	0.100556
HDFC	0.1	0.134293	0.001019
KOTAKBANK	0.1	0.212987	0.048596
AXISBANK	0.1	0.019966	0.029816
SBIN	0.1	0.025269	0.011026
BAJFINANCE	0.1	0.002448	0.243249
BAJAJFINSV	0.1	0.055421	0.215871
SBILIFE	0.1	0.235425	0.190135
HDFCLIFE	0.1	0.087638	0.067941

Figure 9 The ORP portfolio weights for the financial services sector stocks (see online version for colours)

Figure 9 depicts the weight allocation to the financial services sector stocks done by the ORP.

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 23. It is evident that the ORP yields the highest return and it also exhibits the highest risk.

Table 23 The return and risk of the financial services sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	19.97	16.24	27.61
Portfolio annual risk (%)	24.78	22.23	26.91

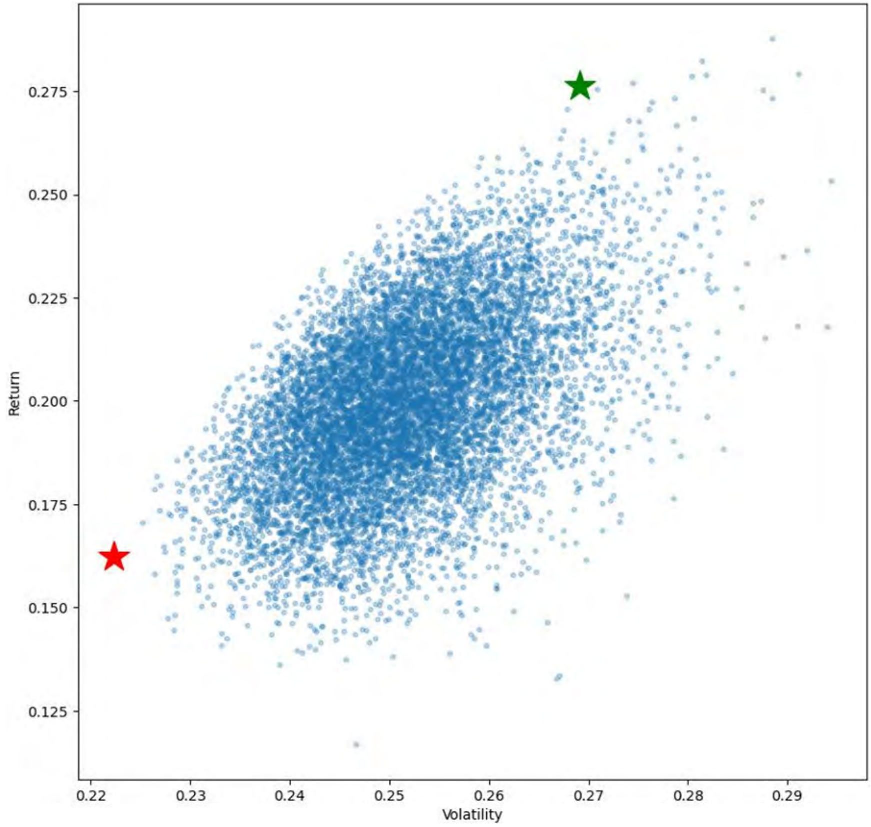
Table 24 The return of the equal-weight portfolio of the financial services sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
HDFCBANK	0.1	1,520	10,000	6.58	1,628	10,714	5.94%
ICICIBANK	0.1	765	10,000	13.08	891	11,650	
HDFC	0.1	2,636	10,000	3.79	2,638	10,005	
KOTAKBANK	0.1	1,824	10,000	5.48	1,827	10,015	
AXISBANK	0.1	696	10,000	14.36	934	13,409	
SBIN	0.1	471	10,000	21.24	614	13,035	
BAJFINANCE	0.1	7,220	10,000	1.39	6,575	9,107	
BAJAJFINSV	0.1	1,698	10,000	5.89	1,548	9,115	
SBILIFE	0.1	1,209	10,000	8.27	1,231	10,181	
HDFCLIFE	0.1	651	10,000	15.37	566	8,705	
			100,000			105,936	

Table 25 The return of the ORP of the financial services sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
HDFCBANK	0.091791	1,520	9,179	6.04	1,628	9,834	–0.94%
ICICIBANK	0.100556	765	10,056	13.15	891	11,714	
HDFC	0.001019	2,636	101	0.04	2,638	102	
KOTAKBANK	0.048596	1,824	4,860	2.66	1,827	4,867	
AXISBANK	0.029816	696	2,981	4.28	934	3,998	
SBIN	0.011026	471	1,103	2.34	614	1,437	
BAJFINANCE	0.243249	7,220	24,325	3.37	6,575	22,154	
BAJAJFINSV	0.215871	1,698	21,587	12.71	1,548	19,677	
SBILIFE	0.190135	1,209	19,014	15.72	1,231	19,358	
HDFCLIFE	0.067941	651	6,794	10.44	566	5,914	
			100,000			99,055	

Figure 10 The efficient frontier of the financial services sector portfolios (see online version for colours)



The return of the equal-weight portfolio of the financial services sector stocks for an investor, investing INR100,000 on 3 January 2022, is shown in Table 24. The investor receives a return of 5.94% at the end of the 12 months.

The performance of the ORP for the financial services sector stocks is shown in Table 25. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be –0.94% indicating a loss for the investor. The negative sign indicates that the investor has suffered a loss.

Finally, the efficient frontier for the financial services sector portfolios is presented in Figure 10. In Figure 10, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the financial services sector. It is to be noted that in Figure 10, the x-axis denotes the risk while the y-axis denotes the return.

4.6 The IT sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 11 and 12 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the IT sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 Tata Consultancy Services (TCS): 26.41.

2 Infosys (INFY): 25.95.

3 HCL Technologies (HCLTECH): 9.49.

4 Wipro (WIPRO): 9.04.

5 Tech Mahindra (TECHM): 8.81.

6 LTI Mindtree (LTIM): 7.67.

7 Persistent Systems (PERSISTENT): 4.52.

8 MphasiS (MPHASIS): 3.29.

9 Coforge (COFORGE): 3.07.

10 L&T Technology Services (LTTS): 1.75.

Table 26 represents the annual return and volatility for the IT sector stocks for the training period from 1 January 2017 to 31 December 2021. PERSISTENT shows the highest annual return while TCS yields the lowest. COFORGE has the highest annual risk while TCS has the lowest.

Table 27 presents the weights allocation to different stocks for the three portfolio design approaches. TCS receives the highest allocation as per the MRP while PERSISTENT receives the highest allocation as per the ORP.

Figure 11 depicts the weight allocation to the IT sector stocks done by the ORP.

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 28. It is evident that the ORP yields the highest return and it also exhibits the highest risk.

The return of the equal-weight portfolio of the IT sector stocks for an investor, investing INR100,000 on 3 January 2022, is shown in Table 29. The investor receives a return of –32.09% at the end of the 12 months. This indicates that the investor has suffered a massive loss using the equal-weight portfolio.

Table 26 The return and risk of the IT sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
INFY	39.88	28.05
TCS	29.34	25.48
HCLTECH	33.02	27.81
TECHM	40.13	31.08
WIPRO	36.67	26.87
LTIM	66.31	34.90
PERSISTENT	85.82	33.93
MPHASIS	54.61	34.10
COFORGE	76.10	43.83
LTTS	62.68	38.15

Table 27 The portfolio weights for the IT sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
INFY	0.1	0.11313	0.085182
TCS	0.1	0.210903	0.004158
HCLTECH	0.1	0.096888	0.085747
TECHM	0.1	0.035844	0.054446
WIPRO	0.1	0.203684	0.024097
LTIM	0.1	0.07319	0.141618
PERSISTENT	0.1	0.171321	0.294376
MPHASIS	0.1	0.070874	0.150793
COFORGE	0.1	0.002889	0.035054
LTTS	0.1	0.021276	0.124528

Figure 11 The ORP portfolio weights for the financial services sector stocks (see online version for colours)

Table 28 The return and risk of the IT sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	52.46	47.79	62.78
Portfolio annual risk (%)	21.14	19.71	22.03

The performance of the ORP for the IT sector stocks is shown in Table 30. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be –31.16% indicating a loss for the investor. Again, the investor has suffered a big loss.

Finally, the efficient frontier for the IT sector portfolios is presented in Figure 12. In Figure 12, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the IT sector. It is to be noted that in Figure 12, the x-axis denotes the risk while the y-axis denotes the return.

Table 29 The return of the equal-weight portfolio of the IT sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
INFY	0.1	1,898	10,000	5.27	1,508	7,944	–32.09%
TCS	0.1	3,818	10,000	2.62	3,257	8,530	
HCLTECH	0.1	1,326	10,000	7.54	1,039	7,837	
TECHM	0.1	1,785	10,000	5.6	1,016	5,695	
WIPRO	0.1	719	10,000	13.91	393	5,465	
LTIM	0.1	7,533	10,000	1.33	4,365	5,795	
PERSISTENT	0.1	4,872	10,000	2.05	3,871	7,945	
MPHASIS	0.1	3,423	10,000	2.92	1,973	5,764	
COFORGE	0.1	5,973	10,000	1.67	3,884	6,503	
LTTS	0.1	5,727	10,000	1.75	3,684	6,432	
			100,000			67,910	

Figure 12 The efficient frontier of the financial services sector portfolios (see online version for colours)

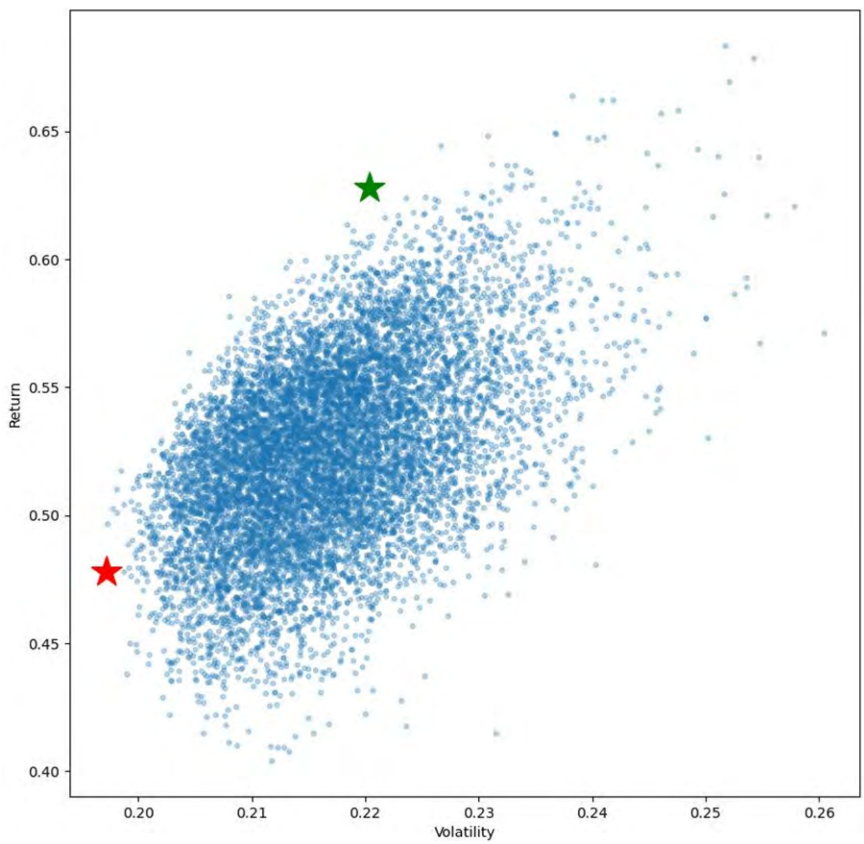


Table 30 The return of the ORP of the IT sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
INFY	0.085182	1,898	8,518	4.49	1,508	6,767	–31.16%
TCS	0.004158	3,818	416	0.11	3,257	355	
HCLTECH	0.085747	1,326	8,575	6.47	1,039	6,720	
TECHM	0.054446	1,785	5,445	3.05	1,016	3,101	
WIPRO	0.024097	719	2,410	3.35	393	1,317	
LTIM	0.141618	7,533	14,161	1.88	4,365	8,207	
PERSISTENT	0.294376	4,872	29,438	6.04	3,871	23,388	
MPHASIS	0.150793	3,423	15,079	4.41	1,973	8,692	
COFORGE	0.035054	5,973	3,505	0.59	3,884	2,279	
LTTS	0.124528	5,727	12,453	2.17	3,684	8,010	
			100,000			68,836	

4.7 The media sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 13 and 14 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the media sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 Zee Entertainment Enterprise (ZEEL): 26.82.

2 PVR (PVR): 24.64.

3 TV18 Broadcast (TV18BRDCST): 9.15.

4 Sun TV Network (SUNTV): 8.91.

5 Dish TV India (DISHTV): 8.07.

6 Nazara Tech (NAZARA): 7.10.

7 Network18 Media & Investments (NETWORK18): 6.52.

8 Navneet Education (NAVNETEDU): 3.68.

9 Hathway Cable and Datacom (HATHWAY): 2.98.

10 NDTV (NDTV): 2.12.

The stock of NAZARA was found to contain more than 30% of its observations missing during the training period from 1 January 2017 to 31 December 2021. The first observation of this stock was available on 30 March 2021. Hence, for NAZARA, only 15% of the observations were available. The computation for the portfolios for the media sector, therefore, did not involve the stock of NAZARA. The remaining nine stocks are used in the portfolio design.

Table 31 represents the annual return and volatility for the media sector stocks for the training period from 1 January 2017 to 31 December 2021. NDTV shows the highest annual return while DISHTV yields the lowest. DISHTV also has the highest annual risk while NAVNETEDUL has the lowest.

Table 31 The return and risk of the media sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
ZEEL	–9.19	53.91
PVR	–0.02	39.66
TV18BRDCST	2.21	50.36
SUNTV	–13.27	39.21
NAVNETEDUL	–12.89	34.08
DISHTV	–19.78	64.21
NETWORK18	31.68	50.79
NDTV	49.24	51.31
HATHWAY	–6.70	58.83

Table 32 The portfolio weights for the media sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
ZEEL	0.1	0.067996	0.063982
PVR	0.1	0.102364	0.057247
TV18BRDCST	0.1	0.031983	0.110087
SUNTV	0.1	0.152141	0.01789
NAVNETEDUL	0.1	0.365526	0.143365
DISHTV	0.1	0.002639	0.008657
NETWORK18	0.1	0.005777	0.317699
NDTV	0.1	0.141213	0.266208
HATHWAY	0.1	0.130359	0.014864

Figure 13 The ORP portfolio weights for the media sector stocks (see online version for colours)

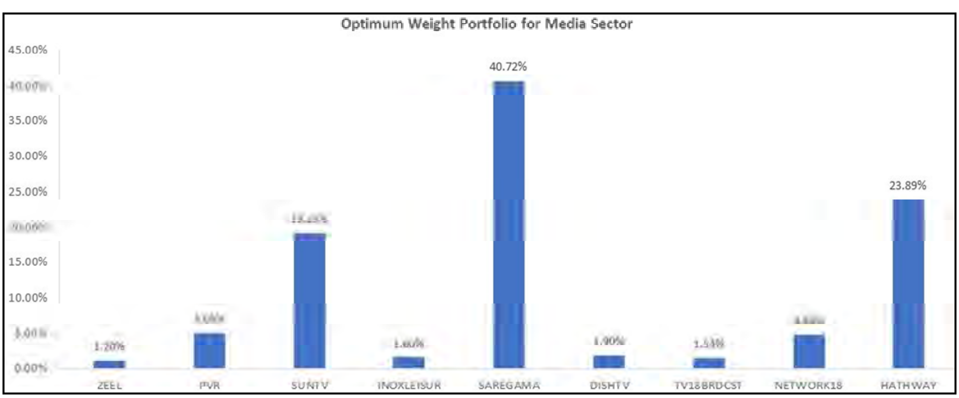


Table 32 presents the weights allocation to different stocks for the three portfolio design approaches. NAVNETEDUL receives the highest allocation as per the MRP while NETWORK18 receives the highest allocation as per the ORP.

Figure 13 depicts the weight allocation to the media sector stocks done by the ORP.

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 33. It is evident that the ORP yields the highest return and it also exhibits the highest risk.

Table 33 The return and risk of the media sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	2.13%	–1.08%	20.47%
Portfolio annual risk (%)	24.66%	24.44%	30.23%

Table 34 The return of the equal-weight portfolio of the media sector stocks

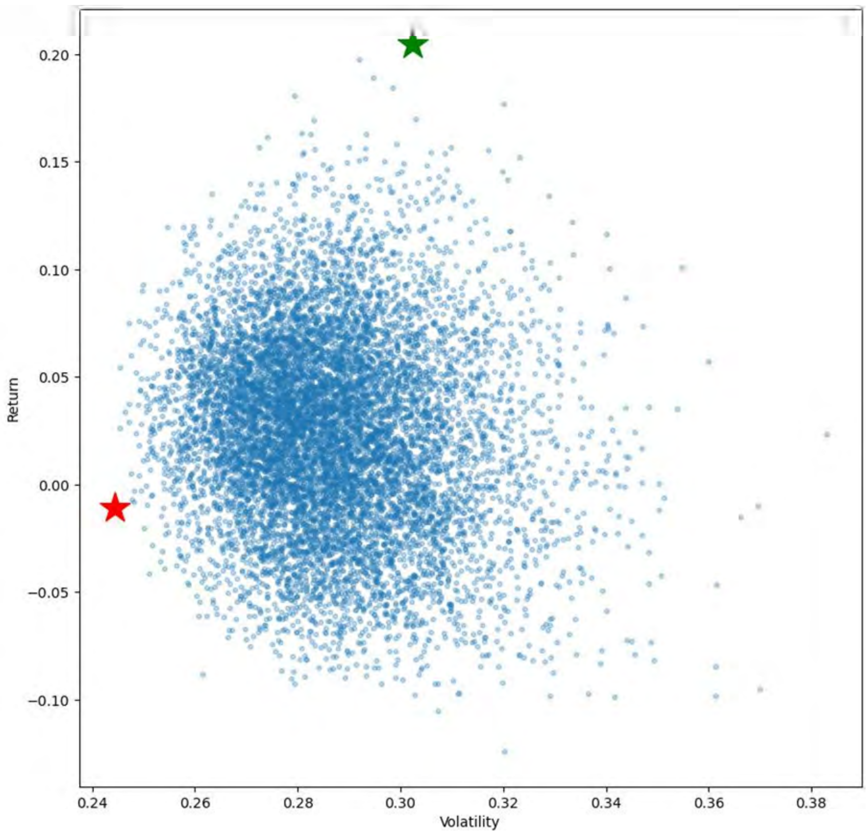
Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
ZEEL	0.1	323	10,000	30.96	240	7,433	–6.13%
PVR	0.1	1,341	10,000	7.46	1,720	12,827	
TV18BRDCST	0.1	504	10,000	19.83	487	9,648	
SUNTV	0.1	355	10,000	28.13	500	14,055	
NAVNETEDUL	0.1	539	10,000	18.56	385	7,152	
DISHTV	0.1	18	10,000	558.66	18	10,279	
NETWORK18	0.1	46	10,000	216.22	37	8,011	
NDTV	0.1	92	10,000	108.87	66	7,197	
HATHWAY	0.1	22	10,000	455.58	17	7,882	
			90,000			84,484	

Table 35 The return of the ORP of the media sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
ZEEL	0.063982	323	6,398	19.81	240	4,756	–17.84%
PVR	0.057247	1,341	5,725	4.27	1,720	7,343	
TV18BRDCST	0.110087	504	11,009	21.83	487	10,621	
SUNTV	0.01789	355	1,789	5.03	500	2,515	
NAVNETEDUL	0.143365	539	14,337	26.6	385	10,253	
DISHTV	0.008657	18	866	48.36	18	890	
NETWORK18	0.317699	46	31,770	686.92	37	25,450	
NDTV	0.266208	92	26,620	289.83	66	19,158	
HATHWAY	0.014864	22	1,486	67.72	17	1,172	
			100,000			82,158	

The annual return for an investor, investing INR100,000 on 3 January 2022, following the EWP approach is shown in Table 34. The annual return in this case is –6.13%. The negative value indicates that the investor has incurred a loss.

Figure 14 The efficient frontier of the media sector portfolios (see online version for colours)



The performance of the ORP for the media sector stocks is shown in Table 35. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be –17.84%, indicating a loss for the investor.

Finally, the efficient frontier for the media sector portfolios is presented in Figure 14. In Figure 14, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the media sector. It is to be noted that in Figure 14, the x-axis denotes the risk while the y-axis denotes the return.

4.8 The metal sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 15 and 16 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the metal sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 Tata Steel (TATASTEEL): 21.98.

2 Adani Enterprises (ADANIENT): 18.52.

3 Hindalco Industries (HINDALCO): 15.57.

4 JSW Steel (JSWSTEEL): 15.37.

5 Vedanta (VEDL): 8.44.

6 Jindal Steel & Power (JINDALSTEL): 5.01.

7 APL Apollo Tubes (APLAPOLLO): 4.48.

8 Steel Authority of India (SAIL): 2.98.

9 Hindustan Zinc (HINDZINC): 1.92.

10 National Aluminium Co. (NATIONALUM): 1.71.

Table 36 represents the annual return and volatility for the metal sector stocks for the training period from 1 January 2017 to 31 December 2021. ADANIENT shows the highest annual return while HINDZINC yields the lowest. JINDALSTEL has the highest annual risk while HINDZINC has the lowest.

Table 37 presents the weights allocation to different stocks for the three portfolio design approaches. HINDZINC receives the highest allocation as per the MRP while ADANIENT receives the highest allocation as per the ORP.

Figure 15 depicts the weight allocation to the metal sector stocks done by the ORP.

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 38. It is evident that the ORP yields the highest return and the equal weights portfolio exhibits the highest risk.

The annual return for an investor, investing INR100,000 on 3 January 2022, following the EWP approach is shown in Table 39. The investor receives a return of 14.38% at the end of the 12 months.

Table 36 The return and risk of metal sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
ADANIENT	123.42	51.96
TATASTEEL	18.57	38.16
JSWSTEEL	28.63	37.70
HINDALCO	21.81	40.81
VEDL	13.49	45.03
JINDALSTEL	20.65	54.52
APLAPOLLO	70.37	39.81
SAIL	13.67	48.64
HINDZINC	3.00	33.98
NATIONALUM	18.98	44.98

Table 37 The portfolio weights for the metal sector stocks

Stock	*EWQ*	*MRP*	*MVP/ORP*
ADANIENT	0.1	0.089969	0.286688
TATASTEEL	0.1	0.125841	0.042599
JSWSTEEL	0.1	0.091772	0.059989
HINDALCO	0.1	0.020789	0.1659
VEDL	0.1	0.047177	0.000744
JINDALSTEL	0.1	0.010119	0.056485
APLAPOLLO	0.1	0.196066	0.251131
SAIL	0.1	0.059842	0.015328
HINDZINC	0.1	0.275785	0.08656
NATIONALUM	0.1	0.082639	0.034577

Figure 15 The ORP portfolio weights for the metal sector stocks (see online version for colours)

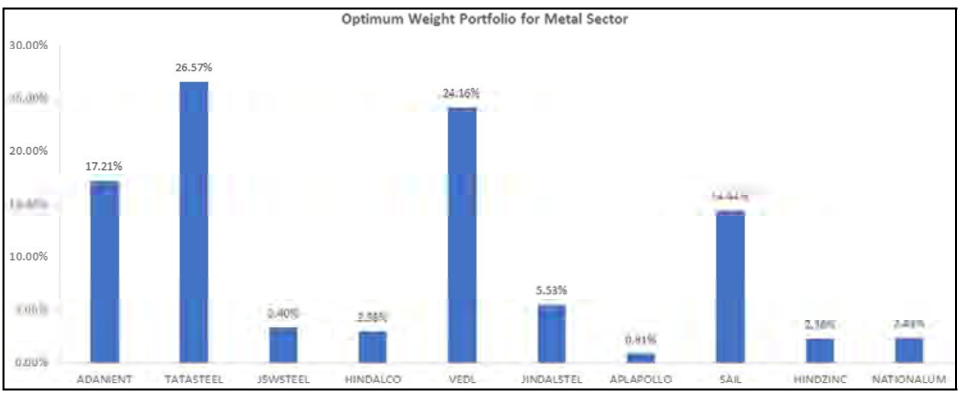


Table 38 The return and risk of the metal sector portfolio

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	33.26	34.38	61.48
Portfolio annual risk (%)	31.64	27.57	30.78

The performance of the ORP for the metal sector stocks is shown in Table 40. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be 41.97% as depicted in Table 40.

Finally, the efficient frontier for the metal sector portfolios is presented in Figure 16. In Figure 16, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the metal sector. It is to be noted that in Figure 16, the x-axis denotes the risk while the y-axis denotes the return.

Table 39 The return of the equal-weight portfolio of the metal sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
ADANIENT	0.1	1,717	10,000	5.82	3,858	22,469	14.38%
TATASTEEL	0.1	114	10,000	87.53	113	9,860	
JSWSTEEL	0.1	667	10,000	14.99	768	11,514	
HINDALCO	0.1	478	10,000	20.92	473	9,902	
VEDL	0.1	354	10,000	28.26	308	8,717	
JINDALSTEL	0.1	386	10,000	25.92	581	15,047	
APLAPOLLO	0.1	949	10,000	10.54	1,092	11,505	
SAIL	0.1	110	10,000	90.83	83	7,507	
HINDZINC	0.1	320	10,000	31.29	322	10,066	
NATIONALUM	0.1	103	10,000	96.95	80	7,794	
			100,000			114,381	

Figure 16 The efficient frontier of the metal sector portfolios (see online version for colours)

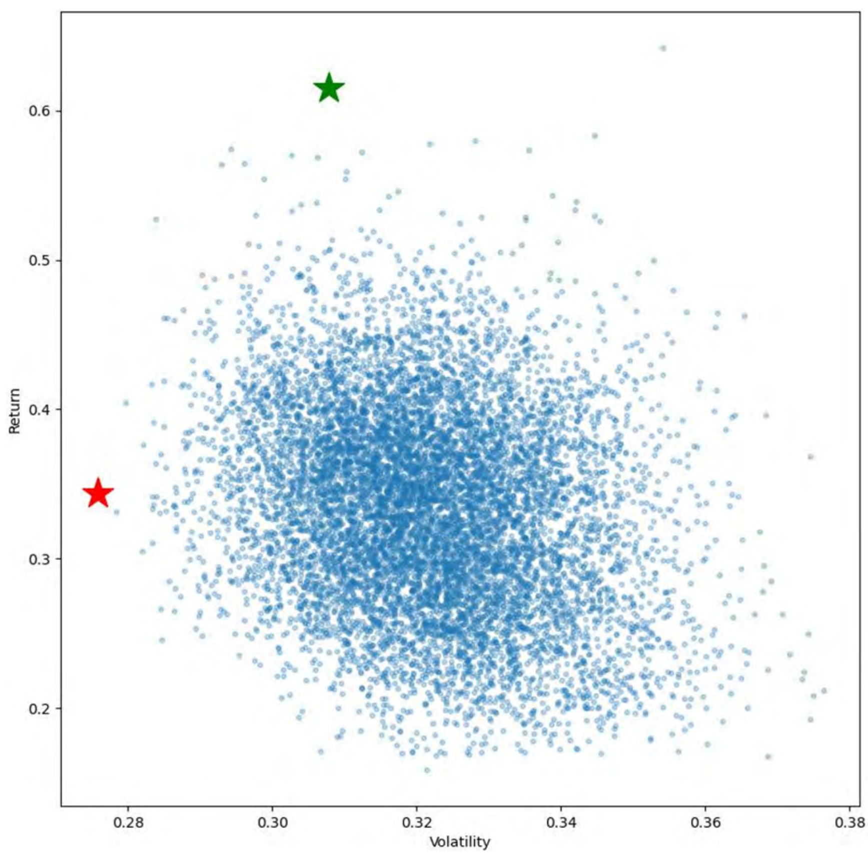


Table 40 The return of the ORP of the metal sector stocks

Stock	Date: 3 January 2022			Date: 31 December 2022			Return
	Weights	Price	Amount invested	No. of stock	Price	Value of stock	
ADANIENT	0.286688	1,717	28,668	16.7	3,858	64,417	41.97%
TATASTEEL	0.042599	114	4,260	37.29	113	4,200	
JSWSTEEL	0.059989	667	5,999	8.99	768	6,907	
HINDALCO	0.1659	478	16,590	34.7	473	16,427	
VEDL	0.000744	354	74	0.21	308	65	
JINDALSTEL	0.056485	386	5,649	14.64	581	8,499	
APLAPOLLO	0.251131	949	25,113	26.46	1,092	28,893	
SAIL	0.015328	110	1,533	13.92	83	1,151	
HINDZINC	0.08656	320	8,656	27.08	322	8,713	
NATIONALUM	0.034577	103	3,458	33.52	80	2,695	
			100,000			141,967	

4.9 *The oil and gas sector portfolios*

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 17 and 18 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the oil and gas sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1. Reliance Industries (RELIANCE): 31.93.
2. Adani Total Gas (ATGL): 12.77.
3. Oil & Natural Gas Corporation (ONGC): 12.44.
4. Bharat Petroleum Corporation (BPCL): 8.15.
5. Indian Oil Corporation (IOC): 7.58.
6. GAIL (India) (GAIL): 6.24.
7. Petronet LNG (PETRONET): 3.96.
8. Hindustan Petroleum Corporation (HINDPETRO): 3.69.
9. Indraprastha Gas (IGL): 3.62.
10. Gujarat Gas (GUJGASLTD): 2.03.

Table 41 represents the annual return and volatility for oil and gas sector stocks for the training period from 1 January 2017 to 31 December 2021. ATGL shows the highest annual return while GAIL yields the lowest. ATGL also exhibits the highest annual risk while PETRONET has the lowest.

Table 41 represents the annual return and volatility for the oil and gas sector stocks for the training period from 1 January 2017 to 31 December 2021. ADANIENT shows the highest annual return while HINDZINC yields the lowest. JINDALSTEL has the highest annual risk while HINDZINC has the lowest.

Table 41 The return and risk of oil and gas sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
RELIANCE	27.11	31.16
ATGL	183.56	55.93
ONGC	–3.00	36.38
BPCL	–3.94	38.96
IOC	–10.70	32.73
GAIL	–7.50	34.34
PETRONET	–3.17	28.56
IGL	12.69	31.51
HINDPETRO	–4.63	42.24
GUJGASLTD	46.02	33.07

Table 42 The portfolio weights for the oil and gas sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
RELIANCE	0.1	0.200318	0.143897
ATGL	0.1	0.029992	0.235186
ONGC	0.1	0.058862	0.004412
BPCL	0.1	0.004858	0.015196
IOC	0.1	0.116086	0.003464
GAIL	0.1	0.055395	0.044979
PETRONET	0.1	0.219963	0.098012
IGL	0.1	0.085547	0.193947
HINDPETRO	0.1	0.039287	0.007842
GUJGASLTD	0.1	0.189693	0.253066

Figure 17 The ORP portfolio weights for the oil and gas sector stocks (see online version for colours)

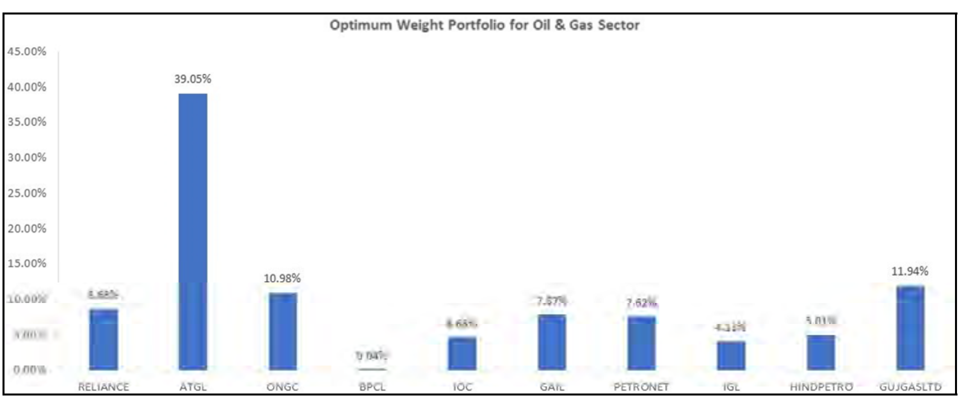


Table 42 presents the weights allocation to the different stocks for the three portfolio design approaches. RELIANCE receives the highest allocation as per the MRP while ATGL receives the highest allocation as per the ORP.

Figure 17 depicts the weight allocation to the oil and gas sector stocks done by the ORP design approach.

Table 43 The return and risk of the oil and gas sector portfolio

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	23.64	18.02	60.38
Portfolio annual risk (%)	23.11	20.39	24.23

Table 44 The return of the equal-weight portfolio of the oil and gas sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
RELIANCE	0.1	2,404	10,000	4.16	2,547	10,596	14.38%
ATGL	0.1	1,744	10,000	5.73	3,693	21,177	
ONGC	0.1	143	10,000	69.91	147	10,259	
BPCL	0.1	386	10,000	25.9	331	8,560	
IOC	0.1	75	10,000	132.8	77	10,159	
GAIL	0.1	88	10,000	114.11	96	10,960	
PETRONET	0.1	219	10,000	45.7	215	9,847	
IGL	0.1	475	10,000	21.06	414	8,718	
HINDPETRO	0.1	297	10,000	33.68	235	7,920	
GUJGASLTD	0.1	641	10,000	15.6	486	7,584	
			100,000			105,780	

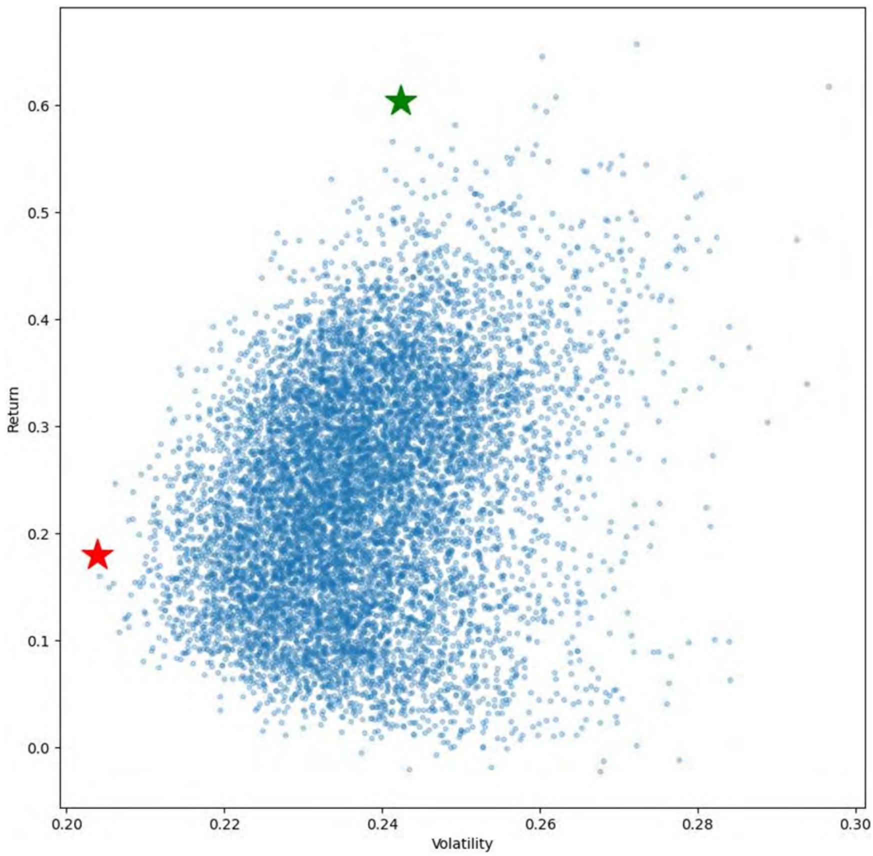
Table 45 The return of ORP of the oil and gas sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
RELIANCE	0.143897	2,404	14,390	5.99	2,547	15,248	18.46%
ATGL	0.235186	1,744	23,519	13.49	3,693	49,805	
ONGC	0.004412	143	441	3.08	147	453	
BPCL	0.015196	386	1,520	3.94	331	1,301	
IOC	0.003464	75	346	4.6	77	352	
GAIL	0.044979	88	4,498	51.33	96	4,930	
PETRONET	0.098012	219	9,801	44.8	215	9,651	
IGL	0.193947	475	19,395	40.85	414	16,909	
HINDPETRO	0.007842	297	784	2.64	235	621	
GUJGASLTD	0.253066	641	25,306	39.48	486	19,193	
			100,000			118,463	

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 43. It is evident that the ORP yields the highest return and it also exhibits the highest risk.

The annual return for an investor, investing INR100,000 on 3 January 2022, following the EWP approach is shown in Table 44. The investor receives a return of 14.38% at the end of the 12 months.

Figure 18 The efficient frontier of the oil and gas sector portfolios (see online version for colours)



The performance of the ORP for the oil and gas sector stocks is shown in Table 45. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be 18.46% as depicted in Table 45.

Finally, the efficient frontier for the oil and gas sector portfolios is presented in Figure 18. In Figure 18, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the oil and gas sector. It is to be noted that in Figure 18, the x-axis denotes the risk while the y-axis denotes the return.

4.10 The pharma sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 19 and 20 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the pharma sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 Sun Pharmaceutical Industries (SUNPHARMA): 26.88.

2 Cipla (CIPLA): 13.25.

3 Dr. Reddy's Laboratories (DRREDDY): 12.65.

4 Divi's Laboratories (DIVISLAB): 10.17.

5 Lupin (LUPIN): 4.28.

6 Alkem Laboratories (ALKEM): 3.55.

7 Torrent Pharmaceuticals (TORNTPHARM): 3.35.

8 Laurus Labs (LAURUSLABS): 3.12.

9 Biocon (BIOCON): 2.80.

10 Aurobindo Pharma (AUROPHARMA): 2.76.

Table 46 represents the annual return and volatility for the pharma sector stocks for the training period from 1 January 2017 to 31 December 2021. LAURUSLABS shows the highest annual return while LUPIN yields the lowest. AUROPHARMA also has the highest annual risk while ALKEM has the lowest.

Table 47 presents the weights allocation to different stocks for the three portfolio design approaches. ALKEM receives the highest allocation as per the MRP while LAURUSLABS receives the highest allocation as per the ORP.

Figure 19 depicts the weight allocation to the pharma sector stocks done by the ORP.

Table 46 The return and risk of the pharma sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
SUNPHARMA	13.89	32.70
CIPLA	16.01	27.90
DRREDDY	23.40	28.60
DIVISLAB	47.35	33.75
LUPIN	2.77	31.15
LAURUSLABS	102.03	36.24
TORNTPHARM	24.45	29.25
ALKEM	15.25	26.28
AUROPHARMA	12.56	40.51
BIOCON	11.82	34.72

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 48. It is evident that the ORP yields the highest return and it also exhibits the highest risk.

The annual return for an investor, investing INR100,000 on 3 January 2022, following the EWP approach is shown in Table 49. The annual return in this case is –14.72%. The negative value indicates that the investor has incurred a loss.

Table 47 The portfolio weights for the pharma sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
SUNPHARMA	0.1	0.088563	0.014507
CIPLA	0.1	0.129415	0.086986
DRREDDY	0.1	0.104707	0.086459
DIVISLAB	0.1	0.063899	0.191804
LUPIN	0.1	0.080866	0.014662
LAURUSLABS	0.1	0.087915	0.281093
TORNTPHARM	0.1	0.118156	0.227336
ALKEM	0.1	0.211195	0.080163
AUROPHARMA	0.1	0.000819	0.004413
BIOCON	0.1	0.114465	0.012578

Figure 19 The ORP portfolio weights for the pharma sector stocks (see online version for colours)

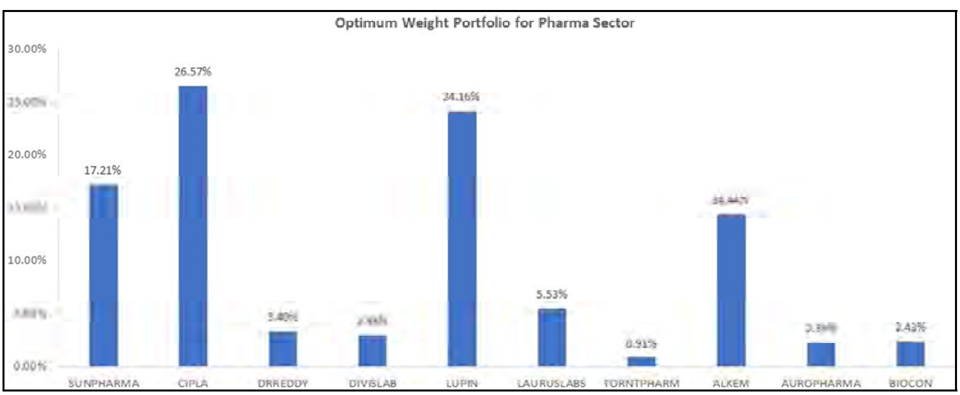


Table 48 The return and risk of the pharma sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	26.95	25.44	48.40
Portfolio annual risk (%)	20.17	18.53	20.80

The performance of the ORP for the pharma sector stocks is shown in Table 50. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return of the ORP over the same period is found to be –16.05%. The investor has incurred a loss using the ORP for the pharma sector.

Table 49 The return of the equal-weight portfolio of the pharma sector stocks

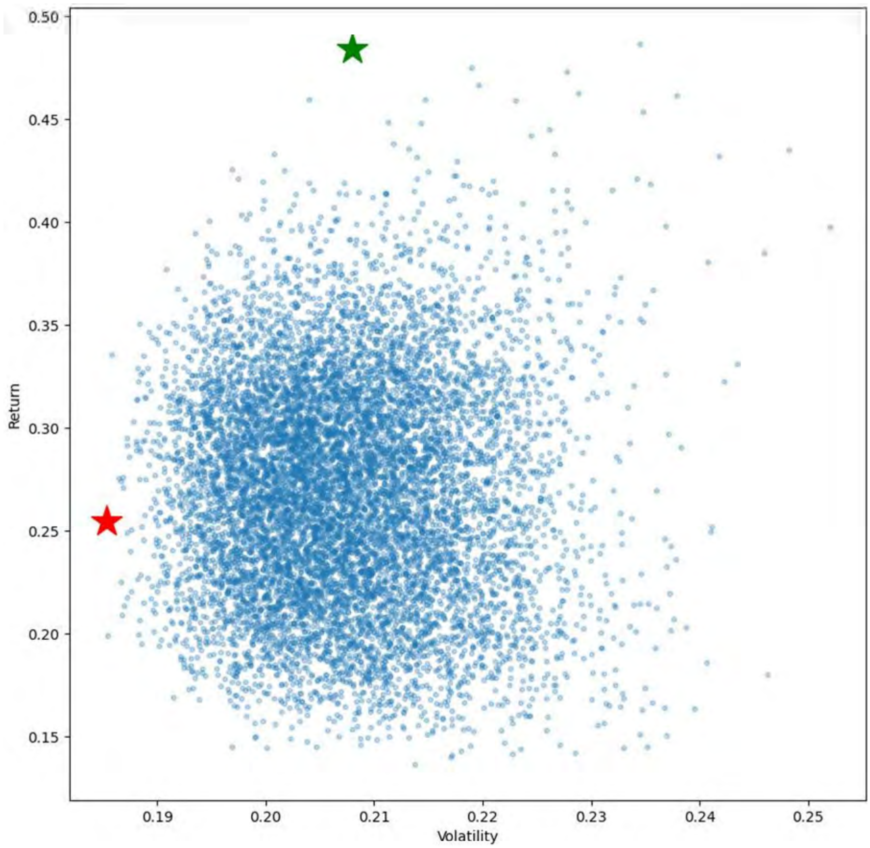
Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
SUNPHARMA	0.1	849	10,000	11.78	1,001	11,796	–14.72%
CIPLA	0.1	931	10,000	10.75	1,076	11,563	
DRREDDY	0.1	4,853	10,000	2.06	4,238	8,732	
DIVISLAB	0.1	4,651	10,000	2.15	3,413	7,338	
LUPIN	0.1	945	10,000	10.58	734	7,762	
LAURUSLABS	0.1	529	10,000	18.91	375	7,097	
TORNTPHARM	0.1	1,626	10,000	6.15	1,551	9,536	
ALKEM	0.1	3,641	10,000	2.75	3,005	8,252	
AUROPHARMA	0.1	732	10,000	13.66	438	5,987	
BIOCON	0.1	363	10,000	27.57	262	7,218	
			100,000			85,281	

Table 50 The return of the ORP of the pharma sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
SUNPHARMA	0.014507	849	1,451	1.71	1,001	1,711	–16.05%
CIPLA	0.086986	931	8,699	9.35	1,076	10,058	
DRREDDY	0.086459	4,853	8,646	1.78	4,238	7,549	
DIVISLAB	0.191804	4,651	19,180	4.12	3,413	14,075	
LUPIN	0.014662	945	1,466	1.55	734	1,138	
LAURUSLABS	0.281093	529	28,109	53.16	375	19,949	
TORNTPHARM	0.227336	1,626	22,734	13.98	1,551	21,679	
ALKEM	0.080163	3,641	8,016	2.2	3,005	6,615	
AUROPHARMA	0.004413	732	441	0.6	438	264	
BIOCON	0.012578	363	1,258	3.47	262	908	
			100,000			83,946	

Finally, the efficient frontier for the pharma sector portfolios is presented in Figure 20. In Figure 20, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the pharma sector. It is to be noted that in Figure 20, the x-axis denotes the risk while the y-axis denotes the return.

Figure 20 The efficient frontier of the pharma sector portfolios (see online version for colours)



4.11 The public sector unit banks portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 21 and 22 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the public sector unit (PSU) bank sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 State Bank of India (SBIN): 29.00.

2 Bank of Baroda (BANKBARODA): 19.56.

3 Canara Bank (CANBK): 12.77.

4 Punjab National Bank (PNB): 12.75.

5 Union Bank of India (UNIONBANK): 7.59.

6 Indian Bank (INDIANB): 6.31.

7 Bank of India (BANKINDIA): 5.36.

8 Indian Overseas Bank (IOB): 1.79.

9 Bank of Maharashtra (MAHABANK): 1.53.

10 Central Bank of India (CENTRALBK): 1.52.

Table 51 represents the annual return and volatility for the training period from 1 January 2017 to 31 December 2021. SBIN shows the highest annual return while PNB yields the lowest. CANBK has the highest annual risk while SBIN has the lowest.

Table 51 represents the annual return and volatility for the PSU bank sector stocks for the training period from 1 January 2017 to 31 December 2021. SBIN shows the highest annual return while PNB yields the lowest. CENTRALBK has the highest annual risk while SBIN has the lowest.

Table 51 The return and risk of the PSU bank sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
SBIN	14.53	36.87
BANKBARODA	–11.65	45.39
CANBK	–7.47	46.69
PNB	–26.96	46.35
UNIONBANK	–20.39	46.36
INDIANB	–11.53	49.46
BANKINDIA	–24.08	47.39
IOB	7.03	44.29
MAHABANK	0.02	46.49
CENTRALBK	–17.39	49.63

Table 52 The portfolio weights for the PSU bank sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
SBIN	0.1	0.213164	0.254636
BANKBARODA	0.1	0.005341	0.040239
CANBK	0.1	0.033512	0.23961
PNB	0.1	0.124246	0.05054
UNIONBANK	0.1	0.034152	0.000181
INDIANB	0.1	0.073182	0.061639
BANKINDIA	0.1	0.026572	0.013106
IOB	0.1	0.120369	0.249011
MAHABANK	0.1	0.194339	0.090445
CENTRALBK	0.1	0.175122	0.000593

Table 52 presents weights allocation to different stocks for the three portfolio design approaches. SBIN receives the highest allocation as per the MRP as well as the ORP.

Figure 21 depicts the weight allocation for the PSU bank sector stocks done by the ORP.

Figure 21 The ORP portfolio weights for the PSU banking sector stocks (see online version for colours)

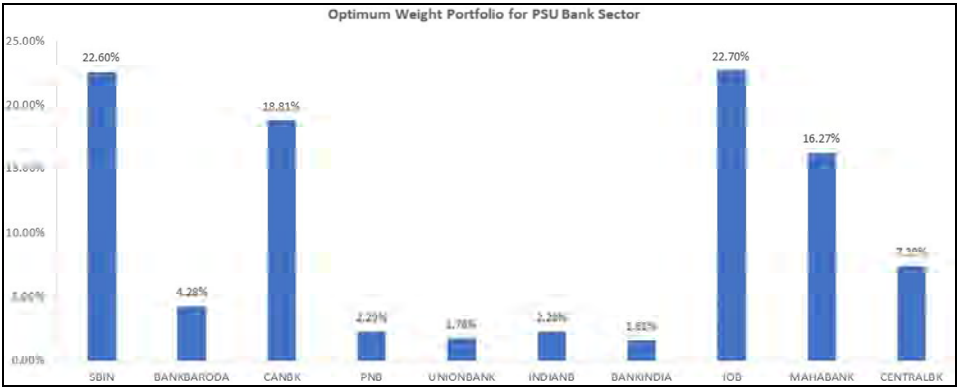


Table 53 The return and risk of the PSU bank sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	–9.79	–4.94	0.79
Portfolio annual risk (%)	35.98	34.12	34.78

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 53. It is evident that the ORP yields the highest return and the equal weights portfolio exhibits the highest risk.

Table 54 The return of the equal-weight portfolio of the PSU bank sector stocks

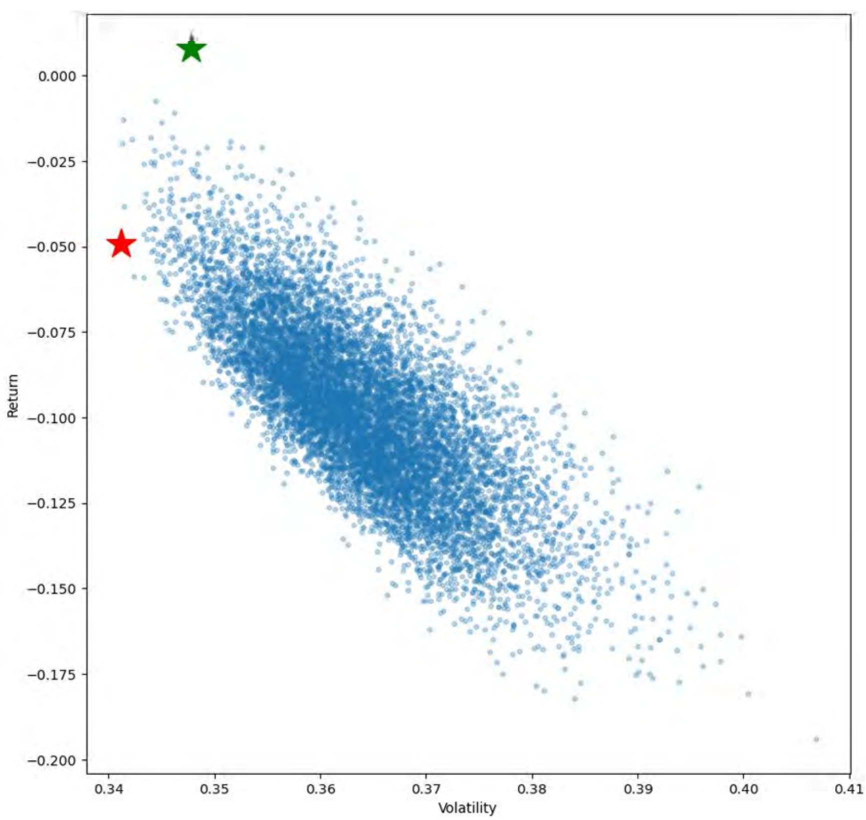
Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
SBIN	0.1	471	10,000	21.24	614	13,035	67.70%
BANKBARODA	0.1	84	10,000	119.33	186	22,160	
CANBK	0.1	205	10,000	48.67	333	16,223	
PNB	0.1	38	10,000	263.16	56	14,855	
UNIONBANK	0.1	44	10,000	226.5	80	18,211	
INDIANB	0.1	142	10,000	70.35	285	20,074	
BANKINDIA	0.1	53	10,000	189.93	88	16,762	
IOB	0.1	21	10,000	486.62	32	15,620	
MAHABANK	0.1	19	10,000	515.46	31	15,773	
CENTRALBK	0.1	21	10,000	466.2	32	14,988	
			100,000			167,701	

The annual return for an investor, investing INR100,000 on 3 January 2022, and following the EWP approach is shown in Table 54. The investor receives a return of 67.70% at the end of the 12 months.

Table 55 The return of the ORP of the PSU bank sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
SBIN	0.254636	471	25,464	54.09	614	33,192	56.34%
BANKBARODA	0.040239	84	4,024	48.02	186	8,917	
CANBK	0.23961	205	23,961	116.63	333	38,872	
PNB	0.05054	38	5,054	133	56	7,508	
UNIONBANK	0.000181	44	18	0.41	80	33	
INDIANB	0.061639	142	6,164	43.36	285	12,373	
BANKINDIA	0.013106	53	1,311	24.89	88	2,197	
IOB	0.249011	21	24,900	1,211.73	32	38,897	
MAHABANK	0.090445	19	9,045	466.21	31	14,266	
CENTRALBK	0.000593	21	59	2.76	32	89	
			100,000			156,344	

Figure 22 The efficient frontier of the PSU bank sector portfolio (see online version for colours)



The performance of the ORP for the PSU bank sector stocks is shown in Table 55. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be 56.34% as depicted in Table 55.

Finally, the efficient frontier for the PSU bank sector portfolios is presented in Figure 22. In Figure 22, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the PSU banks sector. It is to be noted that in Figure 22, the x-axis denotes the risk while the y-axis denotes the return.

4.12 The private (PVT) banks sector portfolios

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 23 and 24 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the PVT bank sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1. HDFC Bank (HDFCBANK): 26.83.
2. ICICI Bank (ICICIBANK): 24.58.
3. Kotak Mahindra Bank (KOTAKBANK): 10.63.
4. Axis Bank (AXISBANK): 10.45.
5. IndusInd Bank (INDUSINDBK): 10.07.
6. Federal Bank (FEDERALBNK): 5.81.
7. Bandhan Bank (BANDHANBNK): 3.78.
8. IDFC First Bank (IDFCFIRSTB): 3.63.
9. City Union Bank (CUB): 2.33.
10. RBL Bank (RBLBANK): 1.89.

Table 56 represents the annual return and volatility for the PVT bank sector stocks for the training period from 1 January 2017 to 31 December 2021. ICICIBANK produces the highest annual return while RBLBANK yields the lowest return. BANDHANBNK exhibits the highest annual risk while HDFCBANK exhibits the lowest volatility.

Table 57 presents the weights allocation to different stocks for the three portfolio design approaches. HDFCBANK receives the highest allocation as per the MRP while ICICIBANK receives the highest allocation as per the ORP.

Figure 23 depicts the weight allocation to the PVT bank sector stocks done by the ORP.

The risk and return values for the three portfolios, computed using the stock prices over the training period, are depicted in Table 58. It is evident that the ORP yields the highest return and the equal weights portfolio exhibits the highest risk.

Table 56 The return and risk of PVT bank sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
HDFCBANK	12.28	24.91
ICICIBANK	25.49	35.63
AXISBANK	5.80	38.54
KOTAKBANK	16.73	29.28
INDUSINDBK	–12.52	48.43
FEDERALBNK	–4.87	40.64
IDFCFIRSTB	–0.85	41.21
BANDHANBNK	–21.88	56.42
CUB	–2.25	34.05
RBLBANK	–26.30	49.44

Table 57 The portfolio weights for the PVT bank sector

Stock	*EWP*	*MRP*	*MVP/ORP*
HDFCBANK	0.1	0.325157	0.204524
ICICIBANK	0.1	0.045523	0.264651
AXISBANK	0.1	0.061599	0.070239
KOTAKBANK	0.1	0.155792	0.230697
INDUSINDBK	0.1	0.0113	0.035574
FEDERALBNK	0.1	0.000128	0.028255
IDFCFIRSTB	0.1	0.096205	0.026738
BANDHANBNK	0.1	0.056141	0.045185
CUB	0.1	0.195319	0.059839
RBLBANK	0.1	0.052836	0.034298

Figure 23 The ORP portfolio weights for the PVT bank sector stocks (see online version for colours)

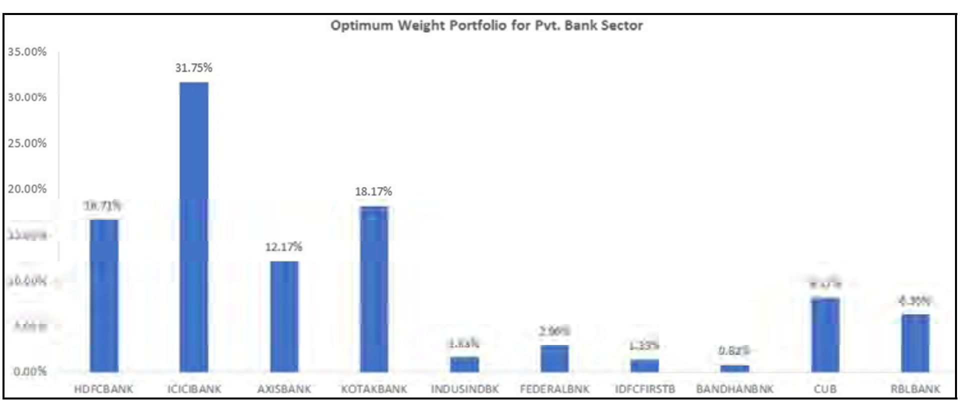


Table 58 The return and risk of PVT bank sector portfolio

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	–0.84	4.84	10.89
Portfolio annual risk (%)	29.05	24.22	25.75

Table 59 The return of the equal-weight portfolio of the PVT bank sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
HDFCBANK	0.1	1,520	10,000	6.58	1,628	10,714	22.76%
ICICIBANK	0.1	765	10,000	13.08	891	11,650	
AXISBANK	0.1	696	10,000	14.36	934	13,409	
KOTAKBANK	0.1	1,824	10,000	5.48	1,827	10,015	
INDUSINDBK	0.1	912	10,000	10.96	1,220	13,374	
FEDERALBNK	0.1	87	10,000	114.68	139	15,946	
IDFCFIRSTB	0.1	50	10,000	201.41	59	11,843	
BANDHANBNK	0.1	252	10,000	39.62	234	9,279	
CUB	0.1	139	10,000	72.15	180	13,016	
RBLBANK	0.1	133	10,000	75.33	179	13,514	
			100,000			122,760	

The annual return for an investor, investing INR100,000 on 3 January 2022, and following the equal-weight portfolio approach is shown in Table 59. The investor receives a return of 22.76% at the end of the 12 months.

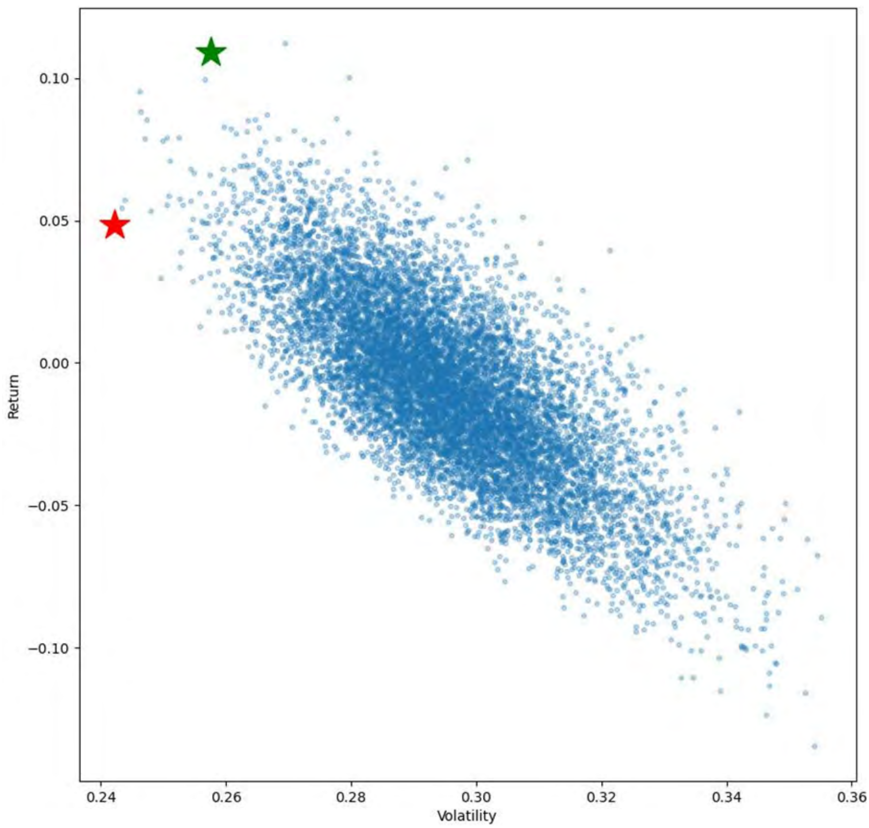
Table 60 The return of the ORP of the PVT bank sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
HDFCBANK	0.204524	1,520	20,452	13.46	1,628	21,913	14.31%
ICICIBANK	0.264651	765	26,465	34.61	891	30,831	
AXISBANK	0.070239	696	7,024	10.09	934	9,418	
KOTAKBANK	0.230697	1,824	23,070	12.64	1,827	23,105	
INDUSINDBK	0.035574	912	3,557	3.9	1,220	4,758	
FEDERALBNK	0.028255	87	2,826	32.4	139	4,506	
IDFCFIRSTB	0.026738	50	2,674	53.85	59	3,167	
BANDHANBNK	0.045185	252	4,518	17.9	234	4,193	
CUB	0.059839	139	5,984	43.17	180	7,789	
RBLBANK	0.034298	133	3,430	25.84	179	4,635	
			100,000			114,315	

The performance of the ORP for the PVT bank sector stocks is shown in Table 60. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be 14.31% as depicted in Table 60.

Finally, the efficient frontier for the PVT bank sector portfolios is presented in Figure 24. In Figure 24, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the PVT banks sector. It is to be noted that in Figure 24, the x-axis denotes the risk while the y-axis denotes the return.

Figure 24 The efficient frontier of the PVT bank sector portfolio (see online version for colours)



4.13 The realty sector portfolio

Following are the top ten stocks of this sector based on their free-float market capitalisation in the NSE, as per the report released on 30 December 2022. Figures 25 and 26 represent the contributions in percentage, of the stocks (computed based on the market capitalisation) to the overall index of the realty sector. The ticker name is also mentioned with a pair of parentheses just beside the name of the respective stock.

1 DLF (DLF): 25.45.

2 Godrej Properties (GODREJPROP): 15.31.

3 Phoenix Mills (PHOENIXLTD): 14.67.

4 Oberoi Realty (OBEROIRLTY): 11.67.

5 Macrotech Developers (LODHA): 11.55.

6 Prestige Estate Projects (PRESTIGE): 7.37.

7 Brigade Enterprises (BRIGADE): 6.66.

8 Indiabulls Real Estate (IBREALEST): 3.21.

9 Sobha (SOBHA): 2.43.

10 Sunteck Realty (SUNTECK): 1.70.

The stock of LODHA was found to contain more than 30% of its observations missing during the training period from 1 January 2017 to 31 December 2021. The first observation of this stock was available on 19 April 2021. Hence, for LODHA, only 15% of the observations were available. The computation for the portfolios for the realty sector, therefore, did not involve the stock of LODHA. The remaining nine stocks are used in the portfolio design

Table 61 represents the annual return and volatility for the realty sector stocks for the training period from 1 January 2017 to 31 December 2021. BRIGADE shows the highest annual return while SUNTECK yields the lowest. IBREALEST has the highest annual risk while PHOENIXLTD has the lowest.

Table 61 The return and risk of the realty sector stocks

Stock	*Annual return (%)*	*Annual risk (%)*
DLF	16.76%	45.67%
GODREJPROP	30.32%	43.43%
PHOENIXLTD	14.47%	39.63%
OBEROIRLTY	17.41%	41.60%
PRESTIGE	20.01%	49.23%
BRIGADE	32.60%	41.70%
IBREALEST	7.88%	61.60%
SOBHA	20.24%	46.99%
SUNTECK	6.98%	42.84%

Table 62 presents the weights allocation to different stocks for the three portfolio design approaches. PHOENIXLTD receives the highest allocation as per the MRP while SOBHA receives the highest allocation as per the ORP.

Figure 25 depicts the weight allocation to the realty sector stocks done by the ORP.

The risk and return values for the three portfolios, computed using stock prices over the training period, are depicted in Table 63. It is evident that the ORP yields the highest return and it also exhibits the highest risk.

The annual return for an investor, investing INR100,000 on 3rd January 2022 following the EWP approach is shown in Table 64. The annual return in this case is –13.83%. The negative value indicates that the investor has incurred a loss.

Table 62 The portfolio weights for the realty sector stocks

Stock	*EWP*	*MRP*	*MVP/ORP*
DLF	0.1	0.036914	0.000519
GODREJPROP	0.1	0.127042	0.227038
PHOENIXLTD	0.1	0.249625	0.174964
OBEROIRLTY	0.1	0.125977	0.080031
PRESTIGE	0.1	0.056054	0.007363
BRIGADE	0.1	0.153627	0.233699
IBREALEST	0.1	0.034577	0.002699
SOBHA	0.1	0.029097	0.263355
SUNTECK	0.1	0.187087	0.010333

Figure 25 The ORP portfolio weights for the realty sector stocks (see online version for colours)

Table 63 The return and risk of the realty sector portfolios

Metric	*EWP*	*MRP*	*MVP/ORP*
Portfolio annual return (%)	16.67	18.57	24.01
Portfolio annual risk (%)	25.70	26.82	28.67

The performance of the ORP for the realty sector stocks is shown in Table 65. To compare the performance of this portfolio with that of the equal-weight portfolio, the initial amount of investment of INR100,000 is kept constant. The return yielded by the ORP is found to be –11.40%, indicating a loss for the investor.

Finally, the efficient frontier for the realty sector portfolios is presented in Figure 26. In Figure 26, the MRP is denoted by the red star, and the ORP is denoted by the green star. The stock prices from 1 January 2017 to 31 December 2021, are considered in plotting the efficient frontier of the realty sector. It is to be noted that in Figure 26, the x-axis denotes the risk while the y-axis denotes the return.

Table 64 The return of the equal-weight portfolio of the realty sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
DLF	0.1	395	10,000	25.33	375	9,500	–13.83%
GODREJPROP	0.1	1,904	10,000	5.25	1,225	6,434	
PHOENIXLTD	0.1	976	10,000	10.24	1,423	14,571	
OBEROIRLTY	0.1	888	10,000	11.26	868	9,771	
PRESTIGE	0.1	472	10,000	21.17	464	9,812	
BRIGADE	0.1	494	10,000	20.24	465	9,413	
IBREALEST	0.1	163	10,000	61.54	81	4,991	
SOBHA	0.1	887	10,000	11.27	576	6,492	
SUNTECK	0.1	502	10,000	19.93	330	6,572	
			90,000			77,556	

Figure 26 The efficient frontier of the realty sector portfolios (see online version for colours)

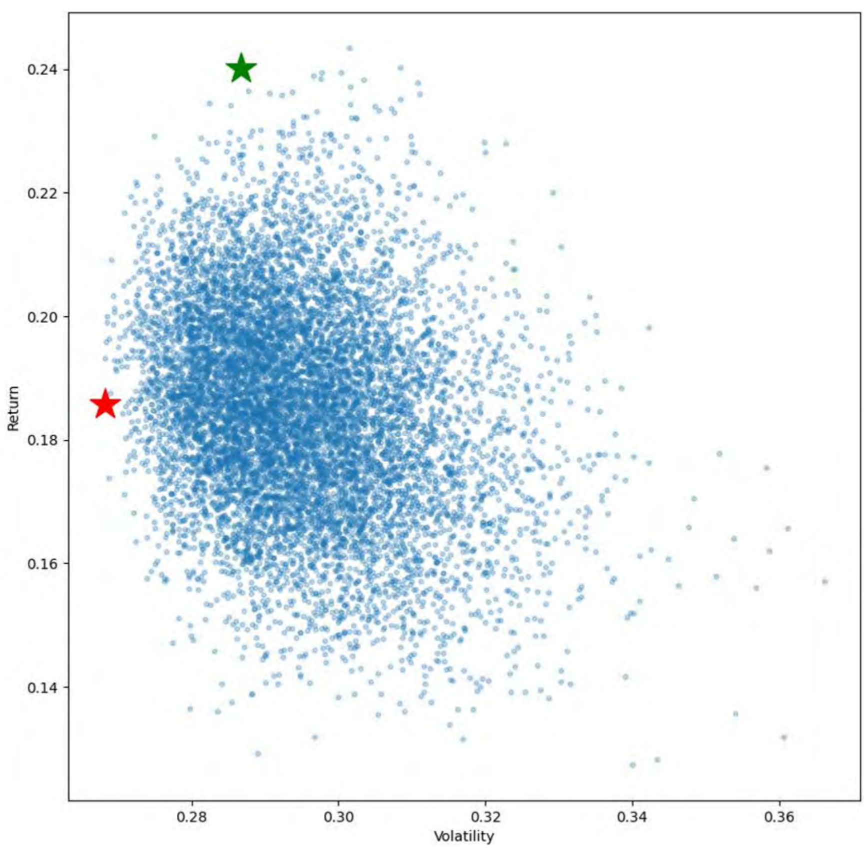


Table 65 The return of the ORP of the realty sector stocks

Stock	*Date: 3 January 2022*			*Date: 31 December 2022*			*Return*
	Weights	*Price*	*Amount invested*	*No. of stock*	*Price*	*Value of stock*	
DLF	0.000519	395	52	0.13	375	49	–11.40%
GODREJPROP	0.227038	1,904	22,704	11.93	1,225	14,607	
PHOENIXLTD	0.174964	976	17,496	17.92	1,423	25,494	
OBEROIRLTY	0.080031	888	8,003	9.01	868	7,820	
PRESTIGE	0.007363	472	736	1.56	464	722	
BRIGADE	0.233699	494	23,370	47.3	465	21,998	
IBREALEST	0.002699	163	270	1.66	81	135	
SOBHA	0.263355	887	26,336	29.68	576	17,098	
SUNTECK	0.010333	502	1,033	2.06	330	679	
			100,000			88,602	

Table 66 The summary of the results of the portfolio performance

Sector	*EWP annual return (%)*	*MVP/ORP annual return (%)*
Auto	23.52	25.78
Banking	34.43	20.25
Consumer durables	–15.74	–20.74
Financial services	5.94	–0.94
FMCG	19.10	30.29
IT	–32.09	–31.16
Media	–6.13	–17.84
Metal	14.38	41.97
Oil and gas	5.78	18.46
Pharma	–14.72	–16.05
Public sector banks	67.70	56.34
Private banks	22.76	14.31
Realty	–13.83	–11.40

4.14 Summary of the results

Table 66 presents a summary of the performance results of the portfolios based on their annual returns over the test period. It is observed that the equal-weight portfolio for the PSU banks yielded the highest return, among all. On the other hand, for the IT sector stocks, the equal-weight portfolio has produced the lowest return. Among the 13 sectors studied in this work, the equal-weight portfolio has yielded a higher return for seven sectors. These sectors are banking, consumer durables, financial services, media, pharma, public sector banks, and private banks. The returns yielded by the ORP are higher for the remaining six sectors. The sectors for which the ORP produced a higher return are auto, FMCG, IT, metal, oil and gas, and realty. Another interesting observation is that there both portfolios have yielded negative returns for a substantial number of sectors. While the equal-weight portfolio has produced five sectors, the number of sectors for which the ORP has yielded negative returns is six. For the financial services sector, the equal-weight portfolio produced a low positive return of 5.94%. However, the return yielded by the ORP for the same sector is negative –0.94%. The five sectors for which both portfolios have yielded negative returns are consumer durables, IT, media, pharma, and realty. Hence, from the investors' point of view, these sectors should be avoided as far as possible till the sentiments in the market change. As a final observation, while the performances of the two portfolio design approaches are found to be similar, the equal-weight portfolio outperformed its optimum risk counterpart by a small margin.

5 Conclusions

Designing a portfolio for optimising the return and risk is a very challenging task. In this paper, two approaches to portfolio design are presented. These approaches are the equal-weight portfolio design and the mean-variance portfolio (also known as the ORP) design. Thirteen important sectors listed on the NSE of India are chosen, and the top ten stocks from each sector are identified based on free-float market capitalisation. Using the historical stock prices for each stock from 1 January 2017 to 31 December 2021, two portfolios are designed for each sector. The portfolios are tested over the stock price data from 1 January 2022 to 31 December 2022. The evaluation of the portfolios is done based on the annual returns yielded by them. It is observed that the returns of the equal-weight portfolio are higher for seven sectors. The sectors for which the equal-weight portfolios have yielded higher returns are banking, consumer durables, financial services, media, pharma, public sector banks, and private banks. However, the ORPs produced higher returns than their equal-weight counterparts for six sectors. These sectors are auto, FMCG, IT, metal, oil and gas, and realty. There are five sectors for which both portfolios are found to have produced negative returns over the year 2022. These sectors are consumer durables, IT, media, pharma, and realty. Investors should avoid investing in the stocks of these sectors to avoid loss till the sentiments in the Indian stock market takes a positive turn. Overall, the public sector banks sector yielded the highest return and is found to be the most profitable one. On the other hand, the IT sector has yielded the highest negative return, and hence, this sector looks to be very risky and should be avoided by investors until the Indian stock market sentiments enter into a bull phase. Comparing the performances of the portfolios designed based on other approaches such as hierarchical risk parity (HRP), eigen portfolios based on principal component analysis, Black-Litterman portfolio, and hierarchical equal risk contribution (HERC) portfolios on these 13 sectors and the stocks listed in NIFTY 50 constitutes a future research work.

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