Decision Making: Applications in Management and Engineering
ISSN: 2560-6018
eISSN: 2620-0104
DOI: https://doi.org/10.31181/dmame0318062021g

AN INTEGRATED FRAMEWORK FOR CLASSIFICATION AND SELECTION OF STOCKS FOR PORTFOLIO CONSTRUCTION: EVIDENCE FROM NSE, INDIA

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Received: 15 November 2021;
Accepted: 16 February 2022;
Available online: 18 June 2022.

Original scientific paper

Abstract: *Investment decision making is a complex process, influenced by a number of conflicting objectives. Investors want to maximize their wealth through investing in the stock market while offsetting the risk to the extent possible. To a common investor, risk is an important aspect to be minimized. In this paper we present a distant framework of stock selection for portfolio construction combining Bayesian classifier and a widely used Multi-Criteria Decision Making (MCDM) technique such as the Technique for order of performance by similarity to ideal solution (TOPSIS) along with Entropy method. The study period is 2013 to 2020. We formulate our research design by considering risk adjusted ratios like Sharpe Ratio, Treynor Ratio, Information Ratio, Jensen Ratio, and Calmar Ratio to compare the NSE 100 listed stocks. Using DP omnibus test, the desired sample of companies following the non-normal distribution was achieved. Using financial beta, we have selected the outcome based on the nature of their 'return' and 'risk'. The Entropy-TOPSIS framework has been used to study the profitability of stocks, rank wise for each year, and finally, the Bayes portfolio model help to select the overall profitability associate with low risk for the construction of the portfolio. We notice year wise inconsistency among the performance of the stocks.*

Key words: Portfolio Selection, Equity Stocks, Bayesian Method, DP Omnibus Test, Risk adjusted return ratios, MCDM, Entropy, TOPSIS.

1. Introduction

Stock market (SM), more specifically the equity market has been an area of interest to the researchers, practitioners and common investors over many decades. There has

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been a plethora of research work conducted on formulation of investment and/or trading strategy to optimize the risk and return at a given level of invested amount. The selection of appropriate stocks and prudent allocation of the total funds among them lead to an effective portfolio management which stands as a cornerstone of successful investment strategy (Ren et al., 2017). Portfolio construction is a complicated task for the common investors considering the up and down- trend of the market. There are a number of considerations of the common investors while selecting the stocks such as high return, low risk, and appropriate time to enter and exit the market, period of holding the stocks, and selection of the sectors among others.

The extant literature is rife in significant contributions in the stated field of security analysis and portfolio management (SAPM) by various scholars in the modern era started with the two seminal work such as concepts and guidelines for security analysis and value investing (Graham et al., 1934) and mean-variance analysis based portfolio selection (Markowitz, 1952). In subsequent years, the growing field of SAPM was notably contributed and expanded by Sharpe (1964), Lintner (1965), Mossin (1966), and Black (1993) (capital asset price model and market equilibrium); Fama (1970) (Efficiency and equilibrium of capital markets); Stattman (1980), Banz (1981), Reinganum (1981), Basu (1983), Rosenberg et al. (1985), Bhandari (1988), Chan et al. (1991) (Impact of firm characteristics on average stock returns); Fama and French (1992, 1993) (three factor asset pricing model for stock selection); Jegadeesh and Titman (1993), Grinblatt et al. (1995), Cooper et al. (2004) (Momentum and contranian based analysis for stock investment strategy); Carhart (1997) (Four factor asset pricing model); Huang et al. (2011) (behavioural bias in selection of stocks); Chong and Phillips (2012), Hsu and Li (2013) (volatility assessment for stock selection); Peachavanish (2016) (integrated fundamental and technical analysis based investment decision making) and Fama and French (2017, 2018) (multifactor model). One generalized view from these research is evident that investors consider multiple perspectives such as market performance indicators like price to earnings ratios, price to book value ratio, beta, return, and volatility, fundamental attributes like return on investment, return on net worth, asset size etc., and technical indicators while formulating their portfolios.

There have been efforts in applying classification models for selection of stocks to invest. Cluster analysis in various forms have been used in several research (for instance, Da Costa et al., 2005; Dose and Cincotti, 2005; Brida and Risso, 2010; Tabak et al., 2010; Silva and Marques, 2010; Nanda et al., 2010; Baser and Saini, 2015; Peachavanish, 2016; Iorio et al., 2018) wherein the analysts considered fundamental and technical attributes for assessing comparative efficiencies and classify the stocks in different categories in the context of global markets (e.g., India, Thailland, Brazil). The advantage of using clustering stems from efficiency based classification of the stocks of varying characteristics that helps in understanding the interplay among the stocks, construction of portfolios with diverse stocks to reduce systematic risk considerably and effective utilization of the funds. In some work (for example, Baks et al., 2001; Cabrera et al., 2018; Jammalamadaka et al., 2019; Hoseini Ebrahimabad et al., 2019; De Rossi et al., 2020; Ampomah et al., 2021; Platanakis et al., 2021) the authors have used Bayesian approach in determining the suitability of the stocks in terms of their market performances and predicted returns vis-à-vis investment decision making.

From the above discussions, it may be inferred that stock selection depends on multiple perspectives that are complex and conflicting in nature. Hence, the extant literature has garnered attentions of the researchers (for instance, Poklepović and Babić, 2014; Vezmelai et al., 2015; Mashayekhi and Omrani, 2016; Hatami-Marbini and

Kangi, 2017; Aouni et al., 2018; Alali and Tolga, 2019; Yildiz, 2020; Peng et al., 2021; Nguyen et al., 2022) and convinced them to apply multi-criteria decision making (MCDM) frameworks in formulation of the investment strategies.

Therefore, it is amply evident from the literature that stock selection for constructing portfolio using the models of predictive analytics inspired by probabilistic and AI/ML concepts, MCDM techniques and statistical analysis are quite common. However, a combined two stage approach based on classification and MCDM models are quite rare in the literature. Further, most of the early work concentrated on market performance indicators, technical analysis and fundamental ratios. The risk adjusted ratios like Sharpe Ratio (SR), Treynor Ratio (TR), and Information Ratio (IR) as used in the present paper have been noticed in use in the literature related to mutual funds.

The present study aims to identify the stocks having low-risk propensities and associated with average to high return to construct a fruitful portfolio allocation for the common investors. We have considered the non-normal stocks from the NSE 100 using some filtering process while disregarding highly volatile stocks. We consider the stocks and its applicability, to investigate portfolio allocation and estimate the potential performance. A TOPSIS based scheme MCDM has been used to classify and select stocks subject to the influence of the financial risk adjusted performance factors and finally using posterior Bayesian optimization for risk less optimal returns.

The research questions (RQ) that the present study endeavours to enquire are

RQ1. Do all stocks (over the study period) follow same type of distribution?

RQ2. What are stocks that follow non-normal distributions?

RQ3. What are the stocks that show low risk propensity associated with average to high return?

RQ4. To what extent do the stocks perform differently on yearly basis over the study period?

In the present study we intend to find answer of the above-mentioned RQs and thereby to suggest a suitable portfolio for the common investors. This paper fills the gap in the literature and contributes in the following ways.

- Firstly, it provides an integrated model for classification and multi-attribute based ranking. In the present study we use the probabilistic Bayesian model in conjunction with MCDM algorithm which seems to be rare in the extant literature.
- Secondly, we use risk adjusted return ratios such as SR, TR, and IR for comparing stock performance.
- Thirdly, in Indian context, the kind of study similar to our work is not available in the literature as we found in our limited search.

The reminder of this paper is presented in the following way. In section 2, we present some of the related work. Section 3 discusses the research methodology while in section 4 the summary of findings is included along with discussions. In section 5 the validation test and sensitivity analysis are included while in section 6 we mention some of the research implications and concluding remarks. Section 7 concludes the paper while highlighting some of the future scope.

2. Related Work

The MCDM algorithms were developed and introduced in the financial market by several researchers Xidonas et al. (2009) reported that MCDM can solve any financial decision, either institutional or private, for investment opportunities. Hurson (1997) performed a comparative analysis among multi-criteria methods such as measuring attractiveness by categorical based evaluation techniques (MACBETH) and multi-utility theory (MUT) for portfolio selection and optimization. In the Croatian stock market a combined framework of COPRAS, linear assignment, PROMETHEE, SAW and TOPSIS was used by Poklepović and Babić (2014). In another study (Vezmelai et al., 2015), the authors considered the criteria like Economic Value Added (EVA), Return on equities (ROE), Return on assets (ROA), Q-Tobin, Earnings per share (EPS) and Price/Earnings per Share (P/E) for conducting a comparative assessment of selected stocks in Tehran Stock market using ELECTRE-III method. Dincer and Hacioglu (2015) used financial stress and conflict risk as the basis for stock selection and applied a combined framework of AHP-TOPSIS-VIKOR. Mashayekhi and Omrani (2016) put forth a trapezoidal fuzzy number based framework of Data Envelopment Analysis (DEA) using the fundamental mean variance model of Markowitz at risk-return interface to derive the efficient portfolio. Bayramoglu and Hamzacebi (2016) carried a fundamental analysis of the stock performance using Grey Relational Analysis (GRA) in the Borsa Istanbul stock exchange, Turkey.

Hatami-Marbini and Kangi (2017) contributed in selecting stocks in untapped sections of Tehran Stock market with future expectation of appreciation of return using new fuzzy distance measures and extension of classical TOPSIS method. A use of multi-objective optimizations is noticed for multi-criteria based stock selection and portfolio optimization following the mean-variance framework in Aouni et al. (2018). Some authors (for instance, Pätäri et al., 2018) have attempted to contribute a comparative framework of several MCDM models to provide the investors best possible way to select the stocks for investing. The work of Makui and Mohammadi (2019) considered behavioural aspects and carried out a comparative analysis of relative utilities for stock selection using UTASTAR method on the basis of risk, return and liquidity. Alali and Tolga (2019) experimented with equally weighted portfolio formulation vis-à-vis the mean-variance one using TODIM method and reported an insignificant benefit of their proposed portfolio. Gupta et al. (2019a) used DEA-COPRAS combination for Portfolio strategy.

Yildiz (2020) applied TOPSIS method for performance analysis of the Turkish stock market indices. There are some other studies in recent past that have used MCDM algorithms for stock selection purpose. For example, Cheng et al. (2021) focused on the sports and leisure industry and used a multi-criteria based decision tree method considering fundamental attributes to propose a stock selection framework. Peng et al. (2021) applied ELECTRE I method in conjunction with Z-numbers for portfolio formulation. The work on Indian IT sector by Ghosh (2021) used a combined framework of Grey Correlational Analysis-AHP-TOPSIS. In the context of Vietnamese market, Nguyen et al. (2022) experimented with CRITIC-DEMATEL method for exploring the impact of Covid-19 on commercial banks. A fuzzy base criterion method and COPRAS was utilized for portfolio selection in the research of Narang et al. (2021). Vásquez et al. (2022) considered an integrated framework of AHP-TOPSIS for portfolio formulation with equity stocks after analysing the performance of Colombian market during the period 2012-2017. In another work (Gupta et al., 2021), a comparative analysis of the financial performance of public sector banks of India has been carried out using a framework of CRITIC-TOPSIS approach.

3. Materials and Method

In this paper we followed a two steps approach. In the first step we classified the stock through a series of filtering. In this process of classification we adopted a probability based approach and applied Bayesian method at the final filtration stage. In initial stage we select financial stocks data from NSE-100 (National Stock Exchange) from March 2013 to March 2020 as per criteria of diversification and applying the filtering process. We consider the stocks which are having non-normal distributions

In the next step, among the final list of selected stocks, we carried a comparative analysis for deriving performance based preferential order based on market perception. The market perception is captured in terms of risk returns based attributed, calculated using closing prices. Therefore in the second stage we applied a widely used multi-attribute decision makes process such as TOPSIS. Finally Bayes portfolio model explains the overall risk on the basis of prior information collected from the outcome of TOPSIS model to construct a fruitful portfolio. Performing the methods step by step we find out portfolio bucket with desire returns with low risk aversion, which may help investor to take decision in portfolio selection.

We introduce a probabilistic approach to estimate the posterior distribution of the target rank conditionally to the predictors. Two desirable properties of a prior distribution for nonparametric problems. (I) the support of the prior distribution should be large--with respect to some suitable topology on the space of probability distributions on the sample space. (II) Posterior distributions given a sample of observations from the true probability distribution should be manageable analytically. The work flow diagram describing the research methodology is given in the figure 1.

3.1. Sample

Out of the 100 selected stocks 14 stocks were discarded because of incomplete data. Table 1 shows all the 86 companies those were ultimately considered initially from the list of NSE 100 companies for this study. As is evident from the Figure 1, we remove 50 stocks from our analysis in the first stage of the filtration process and only 36 stocks having non-normal distribution enters the second stage of the filtration. We then consider financial beta values and the stocks having higher beta values have been discarded as from the perspectives of the common investors we only consider low risk. We get 15 stocks and finally through perceptual mapping we derive our final sample of 6 stocks (having low risk and considerably higher return) for MCDM based comparative analysis.

Table 1: Initial list of 86 companies from NSE 100

S/L	Name	S/L	Name	S/L	Name
1	ACC	31	BPCL	61	HAVELLS
2	ADANIPORTS	32	BRITANNIA	62	HCLTECH
3	AMBUJACEM	33	CADILAHC	63	HDFC
4	ASHOKLEY	34	CIPLA	64	HDFCBANK
5	ASIANPAINT	35	COALINDIA	65	HEROMOTOC
6	AUROPHARMA	36	COLPAL	66	HINDALCO
7	AXIABANK	37	CONCOR	67	HINDPETRO
8	BAJAJFINSV	38	DABUR	68	HINDUNILVR
9	BAJAJHLDNG	39	DIVISLAB	69	HINDZINC
10	BAFINANCE	40	DLF	70	ICICIBANK
11	BANKBARODA	41	DRREDDY	71	IDEA
12	BERGEPAINT	42	EICHERMOT	72	INDUSINDBK
13	BHARTIARTL	43	GAIL	73	INFRATEL
14	BIOCON	44	GODREJCP	74	INFY
15	BOSCHLTD	45	GRASIM	75	IOC
16	ITC	46	PAGEIND	76	TATASTEEL
17	JSWSTEEL	47	PEL	77	TCS

S/L	Name	S/L	Name	S/L	Name
18	KOTAKBANK	48	PETRONET	78	TECHM
19	L&TFH	49	PFC	79	TITAN
20	LUPIN	50	PGHH	80	UBL
21	M&M	51	PIDILTIND	81	ULTRACEMCO
22	MARICO	52	PNB	82	UPL
23	MARUTI	53	POWERGRID	83	VEDL
24	MOTHERSUMI	54	RELIANCE	84	WIPRO
25	NESTLEIND	55	SBIN	85	YESBANK
26	NHPC	56	SHREECEM	86	ZEEL
27	NMDC	57	SIEMENS		
28	NTPC	58	SRTRANSFIN		
29	OFSS	59	SUNPHARMA		
30	ONGC	60	TATAMOTORS		

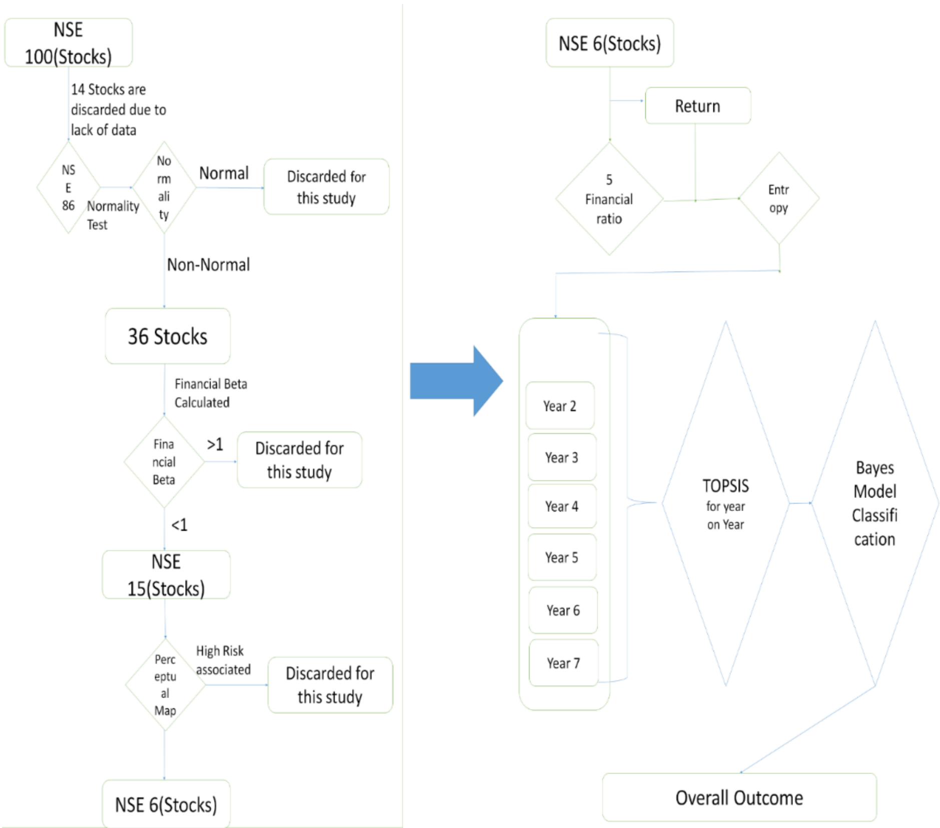


Figure 1. Work Flow Diagram of the Research Methodology

The data are downloaded from NSE website and CMIE Prowess IQ database and company annual reports. Statistical calculations have been done using JAMOVI (version 2.2.5) and R & excel.

3.2. Definitions

a) Financial Beta

Beta is a measure of systematic risk. A beta value of more than 1 indicates that the stock is more unpredictable than the more extensive market and a value under 1 demonstrates that a stock with lower impulsiveness, It is derived from the Capital Asset Pricing Model. Beta is presumably a superior pointer of present moment instead of long term risk.

Traditionally beta coefficient is defined as

$$R_{it} = \alpha + \beta_i R_{mt} + e_{it} \quad (1)$$

Where,
R_{it} is the return on asset i at time t
R_{mt} is the return of the market at time t
α_i and β_i are the intercept and slope (beta)coefficient
The market model is commonly estimated using ordinary least squares regression (OLS). In this instance the OLS estimate of beta is simply:

$$\beta_i = \frac{Cov(R_{it};R_{mt})}{Var(R_{mt})} \quad (2)$$

b) Financial ratios

Financial ratios are the vital indicators helping to find out performance in terms of profitability, liquidity, growth prospect, and stability of a company from its financial reports. Financial ratio can give a blueprint, how an association is performing vis-à-vis its competitors and industry at large. While financial ratios offer useful information about an organization, they should be coordinated with various estimations, to get a broader picture of the company's financial wealth. In this paper we consider market performance of the stocks under study. The ratios used for this paper are briefly described in the following table (see Table 2).

Table 2: Definitions of the ratios used in the paper

Ratio	Formula	Explanation
Sharpe Ratio(SR) (Sharpe 1966)	$SR = \frac{[R_a - R_b]}{\sigma_a}$	$SR = Sharpe\ Ratio,$ $R_a = Assets\ Return,$ $R_b = Risk\ free\ Return,$ $\sigma_a = Standard\ deviation\ of\ the\ asset\ excess\ retu$
Treynor Ratio (TR) (Treynor, 1965)	$TR = (R_a - R_b)/\beta_a$	$TR = Treynor\ Ratio,$ $R_a = Assets\ Return,$ $R_b = Risk\ free\ Return,$ $\beta_a = Assets\ Beta$
Jensen Alpha(JA) (Jensen, 1968)	$\bar{\alpha} = \left(R_a - R_b - \beta_a \times (R_a - R_b)\right)$	$\alpha = Jensen\ Alpha$
Information Ratio (Goodwin, 1998)	$IR = {(R_a - R_c)}/{\sigma_b}$	$R_a = Assets\ Return$ $, R_c = Index\ Return,$ $\sigma_b = Standard\ deviation\ of\ differences$

Ratio	Formula	Explanation
Sortino Ratio(SoR) (Sortino and Van Der Meer, 1991)	$SoR = (R_a - R_b)/\sigma_d$	$\sigma_d = Downside\ risk$
Calmar Ratio(CR) (Young, 1991)	$CR = (R_a - R_b)/D_{max}$	$D_{max} = Maximum\ Draw\ Down$

In the present study we use risk adjusted ratios such as SR that can also be used to determine if a portfolio's excess returns are the consequence of sound investment selections or excessive risk. The standard deviation is a measurement of the square root of the variance and measures the dispersion of a dataset relative to its mean, and its shows how far a portfolio's return deviates from its expected return. The standard deviation also reveals the volatility of the portfolio. When compared to similar portfolios with a lower level of diversification, adding diversification should improve the Sharpe ratio. The Sharpe ratio of a portfolio determines its risk-adjusted-performance. For capturing the market perception, we have followed the risk-return based attribute the ratios which are considered on this paper have mostly being followed in mutual fund assessment. In this respect the present paper at value to the growing literature. Since these ratios consider stocks return, risk-free return, bench mark return, risk parameters.

3.3. Methods

In this sub-section we present the methods used in this paper briefly.

a) DP omnibus test

The normal distribution is the most commonly used distribution when performing statistical procedures and applications, especially for parametric methods, because it is the most widely accepted way to verify normality assumptions. DP omnibus test is best suited for sample sizes between 20 and 1000. The test uses skewness and kurtosis $\sqrt{b1}$ and b2, respectively, and tests for normality of a random sample of the population (Pearson et al., 1977; Wyłomańska et al., 2020). DP Omnibus test used to find out the stocks are follows normal distribution or not. Here in this paper we have selected the stocks, those were non normal in nature, so that we can apply the Bayesian classifier to classify the stocks based on the prior information.
The equation (Yap and Sim, 2011) is shown below.

$$DP = Z^2(\sqrt{b_1}) + Z^2(b_2) \qquad (3)$$

b) 3×3 Investor perceptual Map

It's a graphical representation of an objects to check the position of the items with respect to other items in a two dimensional space, which divides into 9 quadrants. The 9 quadrant are as follows: HL= High Low , HM= High Medium , HH= High High , ML= Medium Low , MM= Medium Medium , MH= Medium High , LL= Low Low , LM= Low Medium and LH= Low High. In this study we have check the position of our stocks on the basis of risk-return interface shown in the figure 2.

Range= Maximum –Minimum. (4)

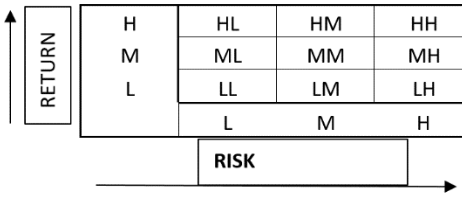


Figure 2: Representation of 3×3 Investor Perceptual Map

c) TOPSIS Method

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a widely popular MCDM algorithm that considers two extreme solution points such as Positive Ideal Solution (PIS) or most optimistic solution and Negative Ideal Solution (NIS) or most pessimistic solution as references (Hwang and Yoon, 1981). The Euclidean distances of 'm' number of alternatives under the influences of 'n' number of criteria are calculated with respect to PIS and NIS. Subsequently, the alternative closest to the PIS (i.e., furthest to NIS) is considered to be the best choice while trading off the impacts of the conflicting criteria. TOPSIS has been used in investment decision making quite frequently (for instance, Vásquez et al., 2022; Hassanzadeh and Valmohammadi, 2021; Atukalp, 2021; Biswas et al., 2019; Gupta et al., 2019; Karmakar et al., 2018). The algorithmic steps for TOPSIS method is given in table 3.

d) Entropy Method

The entropy method is one of the widely used approaches to determine the weights of the criteria using objective information (Biswas et al., 2021; Pramanik et al., 2021; Biswas et al., 2019; Laha and Biswas, 2019; Karmakar et al., 2018). Entropy is essentially a measure of disorder. According to the seminal work of Shannon (1948) on information theory, the entropy method assigns higher weights to the criteria that carry substantial information. The steps are given in the table 4.

e) Bayes Model

Probability is the degree of the prospect that an occasion will occur. Probability is quantified as 0 to 1 (wherein 0 suggests impossibility and 1 suggests certainty). Bayes theorems entails in the pattern space, here occur an event B for which P (B)>0 and the analytics intention is to computes a conditional probability of P (A_k/B). Thomas Bayes (1702-1761) indicates the relation among one conditional probability and its inverse and offer a mathematical rule of revising an estimate for forecast in mild of revel in and observation. In chance idea and facts Bayes theorem (opportunity Bayes regulation and Bayes rule) describes the chance of an occasion primarily based totally on situations that is probably associated with the occasion. Bayesian inference is a technique of statistical inference wherein Bayes theorem is used to replace the chance for a speculation of evidence, it worried with 1) Prior Probability that is preliminary chance primarily based totally on the existing degree of data and 2) posterior chance that is revised chance primarily based totally on extra data, for an unknown parameter θ, its posterior $\pi(\theta \mid x)$ is a conditional distribution of θ below sampler x and it includes all of the data this is available (Avramov, 2002). In this study, collecting the prior information from the outcome of TOPSIS model, we calculate the posterior probability of each stocks considering seven years and find out the overall expected variance of each stocks using Bayes model.

The posterior probabilities is the parameter θ given the evidence $X: p(\theta|X)$ wherein the probability of the evidence is given by the parameter: $p(X|\theta)$.

The probability distribution function is $p(\theta)$ and the observations x have likelihood $p(x|\theta)$.
The equation is:

$$p(\theta|x) = \frac{p(x|\theta)}{p(x)} p(\theta) \tag{5}$$

Where $p(x)$ is the normalizing constant and it's calculated as

$$p(x) = \int p(x|\theta) p(\theta) d\theta \tag{6}$$

For continuous θ or by summing $p(x|\theta)p(\theta)$, the overall possible values of θ for disctete θ.(see; Avramov, 2002)

In this paper we followed a two steps approach. In the first step we classified the stock through a series of filtering. In this process of classification, we adopted a probability based approach and applied Bayesian method at the final filtration stage. In the next step, among the final list of selected stocks, we carried a comparative analysis for deriving performance based preferential order based on market perception. The market perception is captured in terms of risk returns based attributed, calculated using closing prices. Therefore, in the second stage we applied a widely used multi-attribute decision makes process such as TOPSIS. We introduce a probabilistic approach to estimate the posterior distribution of the target rank conditionally to the predictors. Two desirable properties of a prior distribution for nonparametric problems. (I) the support of the prior distribution should be large--with respect to some suitable topology on the space of probability distributions on the sample space. (II) Posterior distributions given a sample of observations from the true probability distribution should be manageable analytically.

Table 4. Computational Steps of Entropy Method

Steps of the Entropy Method	Formula
Step1: Creation of decision matrix	$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$
Step 2: Calculation of the normalized matrix	$p_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad i = 1,2 \ldots \ldots n ; j = 1,2 \ldots . k$
Step 3: Calculation of entropy value	$E_j = -e \sum_{i=1}^{n} p_{ij} , \qquad e = \frac{1}{log\, n} ; j = 1,2 \ldots \ldots k$
Step 4: Determination of entropy weights	$w_i = \frac{d_j}{\sum_{i=1}^{n} d_j} \quad d_j = 1 - E_j ;\ j = 1,2 \ldots . . k$

Table 3. Computational steps of TOPSIS method

Steps	Calculation
Step1: Decision matrix	$Y = \begin{bmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mn} \end{bmatrix}$ m: alternative, n: criteria
Step2: Normalized Matrix	$\overline{Y_{ij}} = \frac{Y_{ij}}{\sqrt{\sum_{j=1}^{n} Y_{ij}^2}}$
Step3: Calculate weighted Normalized Matrix	$V_{ij} = \overline{Y_{ij}} \times W_j$
Step 4: Find out the PIS and NIS	PIS: $V_j^+ = \{Max\, V_{ij}; j \in J^+; Min\, V_{ij}; j \in J^-\}$ NIS $V_j^- = \{Min\, V_{ij}; j \in J^+; Max\, V_{ij}; j \in J^-\}$
Step 5: Calculation Euclidean Distance from the ideal Worst and Best	$d_i^- = \left[\sum_{j=1}^{n} (V_{ij} - V_j^-)^2\right]^{0.5}$ $d_i^+ = \left[\sum_{j=1}^{n} (V_{ij} - V_j^+)^2\right]^{0.5}$
Step 6. Calculation of the Closeness Coefficient	$S_i = \frac{d_i^-}{d_i^+ + d_i^-}$
Decision Rule	Higher the value of S_i, better is the alternative

4. Findings and Discussions

In this section we exhibit step by step data analysis and the findings. First, we calculate the Rate of Return (ROR) of the stocks pertaining to the initial sample of 86 companies. The Rate of Return (ROR) has been calculated from the stocks using the expression followed in Guha et al. (2016).

$$\text{Return } (R_s) = \text{Ln}\left(\frac{l_i}{l_{i-1}}\right).100\% \quad (7)$$

Where l_i the closing price of the current month and l_{i-1} is that of the immediately preceding month. Then the Average RORs (AROR) of all 86 stocks have been calculated by considering the average of the returns of each stock over a period of 84 months as considered in the study (kindly refer Table 5).

Table 5. AROR for the stocks of the initial sample of 86 stocks

Company	RoR	Company	RoR	Company	RoR	Company	RoR
ACC	-0.00214	DRREDDY	0.006775	M&M	-0.00492	TATASTEEL	-0.00119
ADANIPORTS	0.007075	EICHERMOT	-0.00799	MARICO	0.011402	TCS	-0.01277
AMBUJACEM	-0.00134	GAIL	-0.00186	MARUTI	0.014382	TECHM	0.009029
ASHOKLEY	0.008073	GODREJCP	0.008302	MOTHERSUMI	0.005535	TITAN	0.015386
ASIANPAINT	0.01453	GRASIM	0.001052	NESTLEIND	0.015092	UBL	0.003245
AUROPHARMA	0.020639	HAVELLS	0.015676	NHPC	0.00005982	ULTRACEMCO	0.006568
AXIABANK	0.00448	HCLTECH	0.009363	NMDC	-0.00641	UPL	0.017004
BAJAJFINSV	0.021232	HDFC	0.008111	NTPC	-0.00405	VEDL	-0.01044
BAJAJHLDNG	0.008082	HDFCBANK	0.012071	OFSS	-0.0028	WIPRO	0.002169
BAFINANCE	0.035239	HEROMOTOCO	0.000413	ONGC	-0.01323	YESBANK	-0.01596
BANKBARODA	-0.01101	HINDALCO	0.000521	PAGEIND	0.01938	ZEEL	-0.0063
BERGEPAINT	0.023403	HINDPETRO	0.013077	PEL	0.005473		
BHARTIARTL	0.005932	HINDUNILVR	0.020381	PETRONET	0.012869		
BIOCON	0.021195	HINDZINC	0.002949	PFC	0.000209		
BOSCHLTD	0.000533	ICICIBANK	0.006342	PGHH	0.016708		
BPCL	0.010989	IDEA	-0.03688	PIDILTIND	0.019493		
BRITANNIA	0.027699	INDUSINDBK	-0.00168	PNB	-0.01774		
CADILAHC	0.006991	INFRATEL	-0.00133	POWERGRID	0.004857		
CIPLA	0.00128	INFY	0.006839	RELIANCE	0.012601		

Company	RoR	Company	RoR	Company	RoR	Company	RoR
COALINDIA	-0.00942	IOC	0.001765	SBIN	-0.00061		
COLPAL	0.008357	ITC	-0.00219	SHREECEM	0.017473		
CONCOR	0.004894	JSWSTEEL	0.009251	SIEMENS	0.008425		
DABUR	0.014164	KOTAKBANK	0.016412	SRTRANSFIN	-0.00059		
DIVISLAB	0.016588	L&TFH	-0.00433	SUNPHARMA	-0.00179		
DLF	-0.00637	LUPIN	-0.00076	TATAMOTORS	-0.01573		

As seen from the table 5 some stocks (highlighted in light blue shed) have generated negative AROR. We discard those stocks for the next step. It is noticed that the stocks having -ve ARORs exhibited more negative returns during the previous period. From the investors' point of view, a stock generating more number of negative monthly returns given a study period is not promising (Gupta et al., 2019b; Guha et al., 2016). Therefore, we filter out these 28 stocks that lead to a sample of 58 stocks for the next level of the filtration process. In the next step, we run the normality test using the DP omnibus test and select only the stocks which are not having the normal distribution shown (see table 6).

Table 6. Results of the normalization test

Stock No.	1	2	3	4	5	6	7	8	9	10
Normality_ Test	Adaniports	Ashokley	Asianpaint	Aurophrama	Axiabank	Bajajfinsv	Bajajhldng	Bafinance	Bergepaint	Bhartiartl
Omnibus:	14.202	12.354	0.3295	0.7554	58.6075	78.2522	105.2009	27.9473	26.5478	0.495
P value:	0.000824 3	0.002077	0.8481	0.6854	1.88E-13	2.20E-16	2.20E-16	8.54E-07	1.72E-06	0.7807
Stock No.	11	12	13	14	15	16	17	18	19	20
Normality_ Test	Biocon	Boschltd	Bpcl	Britannia	Cadilahc	Cipla	Colpal	Concor	Dabur	Divislab
Omnibus:	2.7371	22.3058	3.6055	40.8193	6.3791	0.2401	4.0566	56.9828	2.3957	36.6359
P value:	0.2545	1.43E-05	0.1648	1.37E-09	0.04119	0.8869	0.1316	4.23E-13	0.3018	1.11E-08
Stock No.	21	22	23	24	25	26	27	28	29	30
Normality_ Test	Drreddy	Godrejcp	Grasim	Havells	Hcltech	Hdfc	Hdfcbank	Heromotoco	Hindalco	Hindpetro
Omnibus:	22.4798	7.0455	47.8567	5.3009	2.2094	22.1051	39.1345	3.7109	49.4638	54.3794
P value:	1.31E-05	0.02952	4.06E-11	0.07062	0.3313	1.59E-05	3.18E-09	0.1564	1.82E-11	1.56E-12

Stock No.	31	32	33	34	35	36	37	38	39	40
Normality_Test	Hindunilvr	Hindzinc	Icicibank	Infy	Ioc	Jswsteel	Kotakbank	Marico	Maruti	Mothersumi
Omnibus:	15.1563	0.2983	24.6786	13.0786	6.1267	29.328	9.6057	54.4598	31.7787	15.1358
P value	0.0005115	0.8615	4.38E-06	0.001446	0.04673	4.28E-07	0.008206	1.49E-12	1.26E-07	0.0005168
Stock No.	41	42	43	44	45	46	47	48	49	50
Normality_Test	Nestleind	Nhpc	Pageind	Pel	Petronet	Pfc	Pghh	Pidilitind	Powergrid	Reliance
Omnibus:	2.001	2.5433	2.9396	9.5742	16.6196	16.8633	1.5921	1.0069	0.5487	32.0946
P value:	0.3677	0.2804	0.23	0.008337	0.0002461	0.0002179	0.4511	0.6044	0.7601	1.07E-07
Stock No.	51	52	53	54	55	56	57	58		
Normality_Test	Shreecem	Siemens	Techm	Titan	Ubl	Ultracemco	Upl	Wipro		
Omnibus:	3.9065	0.8643	5.1705	11.1755	8.9137	1.8214	13.6624	6.0068		
P value:	0.1418	0.6491	0.07538	0.003743	0.0116	0.4022	0.00108	0.04962		

Findings from Table 6 suggest that 36 stocks (in bold font) out of the 58 do not follow the normal distribution pattern and are thus non-parametric in nature. In this study we consider the stocks, those are deviated from the normal distribution as we adopt a non-parametric method for comparative ranking and use the Bayesian classifier. Further we find the financial beta value of each 36 stocks (see table 7).

Table 7. Calculations of Beta values

Stocks	Beta	Stocks	Beta	Stocks	Beta
ADANIPORTS	1.61253	DRREDDY	0.08840	KOTAKBANK	1.09241
ASHOKLEY	1.88335	GODREJCP	1.04473	MARICO	0.24641
AXIABANK	1.88717	GRASIM	0.68448	MARUTI	1.75989
BAJAJFINSV	1.33048	HDFC	1.15587	MOTHERSUMI	1.58371
BAJAJHLDNG	0.93469	HDFCBANK	0.82681	PEL	1.06787
BAFINANCE	1.20713	HINDALCO	1.56231	PETRONET	0.71448
BERGEPAINT	1.1147	HINDPETRO	0.94296	PFC	1.32451
BOSCHLTD	1.41777	HINDUNILVR	0.5529	RELIANCE	0.49102
BRITANNIA	0.49815	ICICIBANK	1.66739	TITAN	1.24017
CADILAHC	0.64286	INFY	0.18335	UBL	0.90054
CONCOR	1.16298	IOC	1.02975	UPL	1.30440
DIVISLAB	0.06692	JSWSTEEL	1.16933	WIPRO	0.17133

In this stage of filtration, we further consider the stocks having beta values ranging less than 1 as higher the beta value, higher is the systematic risk i.e., vulnerability to changes in the macro environment. Therefore, after filtration we get 15 such stocks (highlighted in bold font) having beta values ranging from 0 to 1. In the final stage of the filtration we draw a 3×3 perceptual map (see figure 2).

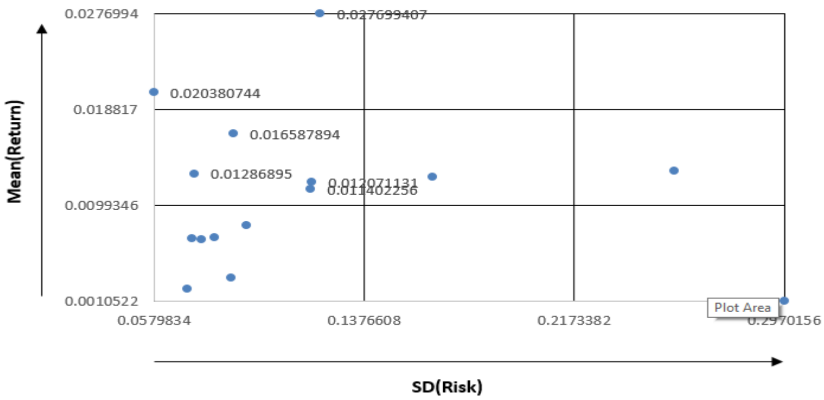


Figure 3. 3×3 investor perceptual map

From the graphical representation of 15 stocks (figure 3) it is evident that 6 stocks are fallen under the quadrants of High Return associated with Low Risk and Medium Return associated with Low Risk are good to invest for the common investor, as the propensity of the risk is low with respect to the other stocks. The six stocks are pointed bold in the table 8 along with their Risk-Return shown below.

Table 8. Formation of the Final Sample of 6 stocks – Risk and return values

Sl.No.	Stocks	SD	Mean
1	BAJAJHLDNG	0.09322	0.00808
2	**BRITANNIA**	**0.1212**	**0.02769**
3	CADILAHC	0.08112	0.00699
4	**DIVISLAB**	**0.0882**	**0.01658**
5	DRREDDY	0.07601	0.00677
6	GRASIM	0.29701	0.00105
7	**HDFCBANK**	**0.11791**	**0.01207**
8	HINDPETRO	0.25536	0.01307
9	**HINDUNILVR**	**0.05798**	**0.02038**
10	INFY	0.07224	0.00683
11	**MARICO**	**0.11756**	**0.0114**
12	**PETRONET**	**0.07332**	**0.01286**
13	RELIANCE	0.16348	0.0126
14	UBL	0.08744	0.00324
15	WIPRO	0.0707	0.00216

The 6 stocks (highlighted in bold fonts) are selected for the final sample for which we apply the integrated framework of Entropy-TOPSIS for year wise comparative assessment. We use the Entropy method to calculate year wise weights of the criteria considered for comparing the stocks (kindly refer table 9). Table 10 shows year wise ranking of the stocks using TOPSIS method.

Table 9. Year wise criteria weights (Entropy method)

Criteria	Entropy_Weights						
	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020
Return	0.06847	0.0153	0.09931	0.09712	0.00938	0.03659	0.06582
Sharp Ratio	0.18526	0.03222	0.20463	0.16162	0.02761	0.23421	0.11928
Treynor Ratio	0.19959	0.10813	0.10712	0.18241	0.40953	0.23555	0.27652
Information Ratio	0.17449	0.25103	0.08701	0.18168	0.24989	0.03676	0.28591
Jensen Ratio	0.17979	0.52342	0.14676	0.20311	0.20539	0.22805	0.16197
Calmar Ratio	0.19236	0.06987	0.35515	0.17403	0.09825	0.22882	0.09048

Table 10. Year wise ranking of the stocks (TOPSIS method)

Stocks	TOPSIS_Rank_Year_on_Year						
	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020
BRITANNIA	1	6	6	4	6	2	5
DIVISLAB	5	5	5	6	5	1	1
HDFCBANK	2	2	1	1	2	5	2
HINDUNILVR	3	4	3	5	1	3	4
MARICO	4	3	4	3	4	4	6
PETRONET	6	1	2	2	3	6	3

In the final stage of the study we find the overall expected rank and expected standard deviation of the stocks based on the prior outcome of TOPSIS method as shown in the table 10.Let Y_t be the discrete random variable of i[th] stock, where i consist with 1 to 6 ie, $Y_{i1} = BRITANNIA$, ……$Y_{i6} = PETRONET$, and P_t is the posterior probability of t[th] years, where t= 1 to 7, which is $\boldsymbol{P_t = (P(E_i) * P(A/E_i)/Sum(P(E_i) * P(A/E_i))}$and A be an event the rank obtain using by TOPSIS methods for each stocks in every year Table 9. The probability of each stocks P(E_i) = 1/7, and $P(A/E_i)$the event where P is random probability of each stocks , A be the rank which is obtain from TOPSIS and E_i is the sum of the rank of stocks for each year i.e. 21, shown in the (Table 11) for the 1[st] stock Britannia. Now we calculate the expected rank for each stocks as E(x)=$\sum Y_t P_t$, where, E(x) is the expectation of rank, Y_t is outcome from TOPSIS of each stocks and P_t is cross-ponding posterior probability of each stocks for 7 years, the rank shows (Table 12) the minimum expectation possible when posterior probability is minimum, and selecting stocks as per the minimum expectation of rank, which investigates for portfolio selection, in this study.

Table 11: Posterior probability for Britannia using Bayes model

BRITANNIA	BRITANNIA	BRITANNIA	BRITANNIA	BRITANNIA	BRITANNIA	BRITANNIA
P(Ei)		Rank		P(A/Ei)	P(Ei)*P(A/Ei)	Pi-> (P(Ei)*P(A/Ei))/Sum(P(Ei)*P(A/Ei))
0.14285	year 1	1	p1	0.05	0.00681	0.03333
0.14285	year 2	6	p2	0.29	0.04081	0.2
0.14285	year 3	6	p3	0.29	0.04081	0.2
0.14285	year 4	4	p4	0.19	0.02721	0.13333
0.14285	year 5	6	p5	0.29	0.04081	0.2
0.14285	year 6	2	p6	0.10	0.01360	0.06666
0.14285	year 7	5	p7	0.24	0.03401	0.16666
					Sum(P(Ei)*P(A/Ei))	Sum
					0.20408	1

Similarly we calculate the posterior probability of other 5 stocks (Shown in the annexure 1).

Table 12: Overall Rank estimation using Bayes model

Stocks	Expected_Rank	Variance	Rank
BRITANNIA	5.13333	11.54046	6
DIVISLAB	4.92857	10.55235	5
HDFCBANK	2.86666	6.15214	1
HINDUNILVR	3.69565	6.8107	2
MARICO	4.21428	8.41918	3
PETRONET	4.30434	10.13146	4

The year on year performance i.e. from 2013 to 2020 of the stocks for constructing portfolio depends on TOPSIS model (Table 10), and finally the Table 12 depicts the overall performance of stocks for portfolio construction by using Bayes model, which will help the common investor to invest their capital with minimum and maximum portfolio weightages as rank-wise for short span (year wise) and long span (overall) on the basis of their perception.

We check the year to year consistency of ranking of the stocks and notice that ranking order varies which is a common phenomenon in the stock market given the changes in the macroeconomic factors. Therefore, we select the ranking order to table 12 as final to formulate the portfolio.

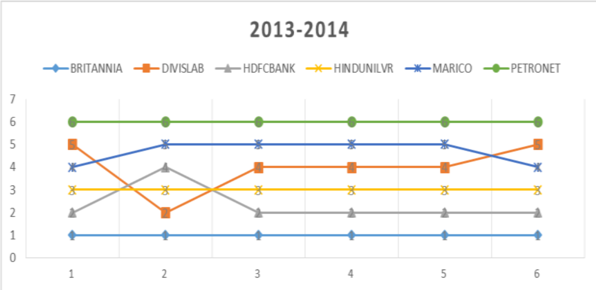
5. Validation and Sensitivity Analysis

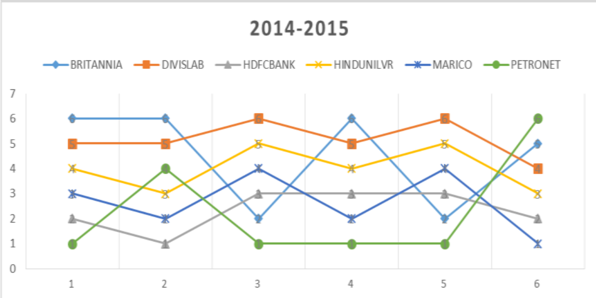
The results obtained using the MCDM models are vulnerable to changes in the given conditions such as criteria selection, inclusion and exclusion of the alternatives, change in the criteria weights, change in the alternative's performance value among others (Biswas, 2020; Biswas et al., 2021a). Hence, it is required to validate the result and perform the sensitivity analysis for examining the stability in result subject to changes in the given conditions (Stević et al., 2020; Mukhametzyanov and Pamucar, 2018; Pamucar et al., 2017).In this paper, for validation purpose, we carry out comparative ranking of the final six stocks using COPRAS method (Zavadskas et al., 2007) and compare the results with that obtained using TOPSIS method for all the years under study as used in Pamucar et al. (2021); Sahu et al. (2021); Varatharajulu et al. (2021); Dehdasht et al. (2020), Si et al. (2020) and Biswas and Anand (2020). Table 13 indicates that ranking orders (among TOPSIS and COPRAS) are considerably consistent year wise that implies the validity of the results.

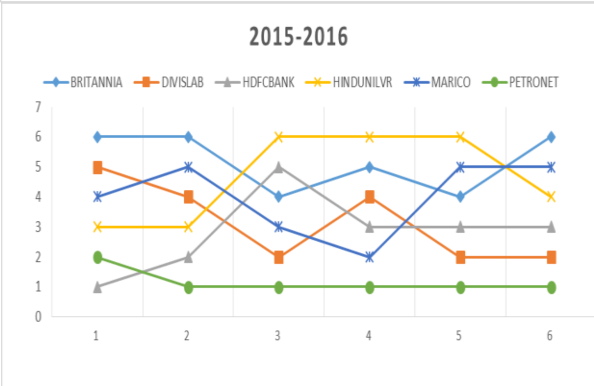
Table 13. Comparison of TOPSIS and COPRAS year wise ranking (validation purpose)

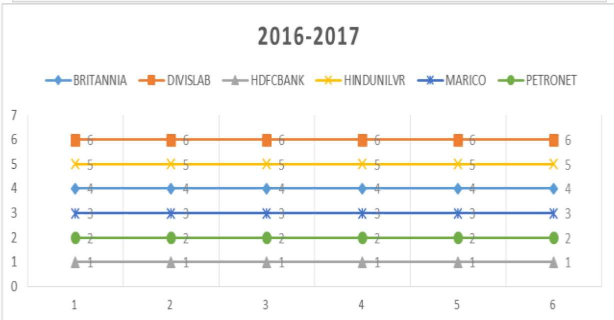
FY	2013-2014		2014-2015		2015-2016		2016-2017	
Method/ Stock	TOPSIS	COPRAS	TOPSIS	COPRAS	TOPSIS	COPRAS	TOPSIS	COP RAS
BRITANNIA	1	1	6	6	6	6	4	4
DIVISLAB	5	5	5	5	5	4	6	6
HDFCBANK	2	2	2	2	1	1	1	1
HINDUNILVR	3	4	4	4	3	3	5	5
MARICO	4	3	3	3	4	5	3	3
PETRONET	6	6	1	1	2	2	2	2
FY	2017-2018		2018-2019		2019-2020			
Method/ Stock	TOPSIS	COPRAS	TOPSIS	COPRAS	TOPSIS	COPRAS		
BRITANNIA	6	6	2	2	5	4		
DIVISLAB	5	5	1	1	1	1		
HDFCBANK	2	2	5	5	2	2		
HINDUNILVR	1	1	3	3	4	5		
MARICO	4	4	4	4	6	6		
PETRONET	3	3	6	6	3	3		

We now move forward to carry out the sensitivity analysis. We follow the approach of Biswas and Anand (2020). Table 14 shows the exchange of weights for 2013-2014 for the six criteria and other year's calculations shown in Annexure file and Table 15 shows the result of the experimentation with exchange of weights among the pair of criteria in five occasions for each FY and figure 4 shows the graphical representation of sensitivity analysis. It is evident from the table 14 and subsequently from the figure 3 that the results are quite stable.


2013-2014
BRITANNIA
DIVISLAB
HDFCBANK
HINDUNILVR
MARICO
PETRONET


2014-2015
BRITANNIA
DIVISLAB
HDFCBANK
HINDUNILVR
MARICO
PETRONET


2015-2016
BRITANNIA
DIVISLAB
HDFCBANK
HINDUNILVR
MARICO
PETRONET


2016-2017
BRITANNIA
DIVISLAB
HDFCBANK
HINDUNILVR
MARICO
PETRONET

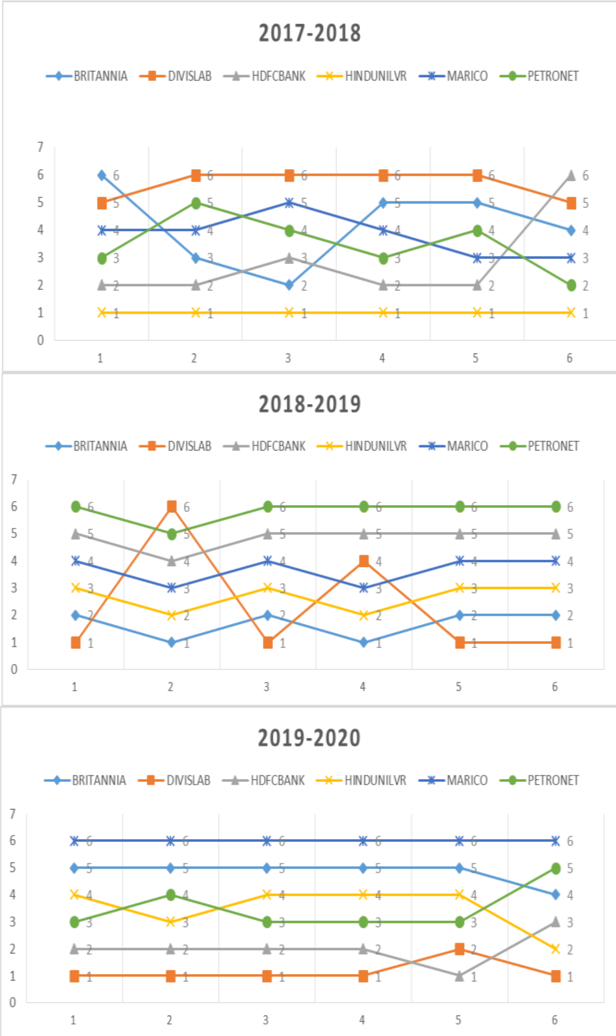


Figure 4. Graphical representation of Sensitivity Analysis

Table 14. Exchange of weight for 2013-2014 for the six criteria

	Weight_exchange					
	Ret	Sharp Ratio	Treynor Ratio	Inforamntion Ratio	Jensen Ratio	Clamar
Original_weight	0.06847	0.18526	0.19959	0.17449	0.17979	0.19236
T1	0.19959	0.18526	0.06847	0.17449	0.17979	0.19236
T2	0.06847	0.19959	0.18526	0.17449	0.17979	0.19236
T3	0.06847	0.18526	0.17449	0.19959	0.17979	0.19236
T4	0.06847	0.18526	0.17979	0.17449	0.19959	0.19236
T5	0.06847	0.18526	0.19236	0.17449	0.17979	0.19959

Other year’s calculations shown in Annexure file.

Table 15. Result of sensitivity analysis

FY	2013-2014						2014-2015						2015-2016					
Stock	Original	T1	T2	T3	T4	T5	Original	T1	T2	T3	T4	T5	Original	T1	T2	T3	T4	T5
BRITANNIA	1	1	1	1	1	1	6	6	2	6	2	5	6	6	4	5	4	6
DIVISLAB	5	2	4	4	4	5	5	5	6	5	6	4	5	4	2	4	2	2
HDFCBANK	2	4	2	2	2	2	2	1	3	3	3	2	1	2	5	3	3	3
HINDUNILVR	3	3	3	3	3	3	4	3	5	4	5	3	3	3	6	6	6	4
MARICO	4	5	5	5	5	4	3	2	4	2	4	1	4	5	3	2	5	5
PETRONET	6	6	6	6	6	6	1	4	1	1	1	6	2	1	1	1	1	1
FY	2016-2017						2017-2018						2018-2019					
Stock	Original	T1	T2	T3	T4	T5	Original	T1	T2	T3	T4	T5	Original	T1	T2	T3	T4	T5
BRITANNIA	4	4	4	4	4	4	6	3	2	5	5	4	2	1	2	1	2	2
DIVISLAB	6	6	6	6	6	6	5	6	6	6	6	5	1	6	1	4	1	1
HDFCBANK	1	1	1	1	1	1	2	2	3	2	2	6	5	4	5	5	5	5
HINDUNILVR	5	5	5	5	5	5	1	1	1	1	1	1	3	2	3	2	3	3
MARICO	3	3	3	3	3	3	4	4	5	4	3	3	4	3	4	3	4	4
PETRONET	2	2	2	2	2	2	3	5	4	3	4	2	6	5	6	6	6	6
FY	2019-2020																	
Stock	Original	T1	T2	T3	T4	T5												
BRITANNIA	5	5	5	5	5	4												
DIVISLAB	1	1	1	1	2	1												
HDFCBANK	2	2	2	2	1	3												
HINDUNILVR	4	3	4	4	4	2												
MARICO	6	6	6	6	6	6												
PETRONET	3	4	3	3	3	5												

6. Research Implications and Conclusion

This article focuses on the simple theorem of homogeneous beliefs of risk-free assets and normal returns for all investors, including those with influence functions, choose investment portfolios, and the combination of risk-free assets. The present work considers non-normally distributed returns and risk-free assets. This objective examines whether investors in influence, companies will choose an effective

investment portfolio when returns are incompletely non-normally distributed and borrow or borrow at risk-free interest rates. Also shows that the unlevered investment portfolio of investors is very close to the beta coefficient, regardless of how the portfolio is constructed; the degree of inter-temporal changes in the portfolio's beta coefficient will decrease as the number of securities in the portfolio increases. However, regardless of whether the investment portfolio is highly concentrated or widely diversified, there are significant differences in the portfolio's speculation capital. After the filtration process on the basis of low risk and potential return, the framework implement TOPSIS method aims to reshape the reality of the portfolio construction process. It is a flexible combined with various data analysis techniques to evaluate financial indicators in the form and check the best possible outcome type for stocks as a ranking wise for decision-making and construction in a multi-dimensional context. The Bayesian portfolio model (one of the most widely used portfolio construction tools) and prior information about improving the efficiency of risk estimation expenditure and managing the uncertainty of the portfolio under the risk conditions of the prior assumptions of the portfolio optimization problem the integration of the potential model for the test dataset.
The advantage of our model is as follows.

- The mean and variance are only the first and second central moments of a random variable and are not sufficient to evaluate the entire distribution of the variable. However, the mean and variance do capture the most important information. Therefore, in order to avoid complexity in calculating higher moments of the variable's distribution, the mean and variance are the only parameters considered in forming the portfolios.
- In finance point of view we have taken only the Risk Assessment Parameter ie. Sharpe ratio, Treynor Ratio, Jensen Alpha, Information Ratio, Sortino Ratio and Calmar Ratio, which are taken as a criteria in decision making model.
- For the Bayesian approach, we need the prior distribution of the stock returns and an updated data set. In this paper we are also derived from the returns of all stocks, consider as a prior information. The prior distribution could be estimated to apply the Bayesian approach, the priors could be categorized into two cases: informative and uninformative. As we notice, in the uninformative case, i.e. not a lot of information is known about the prior distribution. Some hidden parameters can also the affects the constructed model.

7. Future Scope

People always want to make the optimal financial decision. However, many investors ignore the uncertainties of the parameters and models, which lead to a suboptimal portfolio at last. From this point of view, these models may be of some practical significance and enlightenment. Besides, in the future work, we can try to take other informative priors information into consideration, try to expand the models to the multi-stage situation, or even try other frameworks instead of mean-variance framework, such as the utility function, safety-first framework, and so on. In addition, one of our limitation of our study is that as we are only concentrated on the technical parameter of the stocks and exclude the fundamental parameter like Return on Equity, Return on Capital Employed, EVA etc. this gap can be address in the future study. Further work to extend and improve the methodology proposed in this paper should focus on four points: (a) Methodologies in web-based decision-making information systems to support investment decisions in real time (b) choosing decision making weights from entropy to AHP c) Taking into account a decision-making parameters such as quality of management decision and the company's fundamental position in the market, set as a criteria in a qualitative direction, and (d) expand the focus of the methodology to include additional asset classes. Further, TOPSIS model sometimes may be suffering from rank reversal problem. Hence, more checking is required. Nevertheless, this paper shows a considerably unique approach of classification and ranking of stocks for portfolio selection which we hope to be of use to the individual investors and policy makers.

Author Contributions: Author Contribution: Conceptualization, S.G, G.B, S.B and A.M.; methodology, S.G and G.B.; software, S.G and A.M; validation, S.G., G.B. and S.B; formal analysis, S.G and G.B; investigation, S.G, S.B; resources, S.G, G.B.; data curation, S.B. and A.M.; writing—original draft preparation, S.B, S.G. and A.M.; writing—review and editing, S.G., G.B and S.B; visualization, S.G and A.M.; supervision, G.B; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflicts of interest.

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