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Portfolio Selection using DEA-COPRAS at Risk – Return Interface Based on NSE (India)

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Abstract*: Portfolio formation holds paramount importance in the process of the investment decision making since, a single door investment (SDI) option is much riskier than a multiple door investment (MDI) option. Among available financial instruments, the stock market (SM) has allured investors because of its liquidity and growth opportunities. However, the effectiveness of the investment decision is largely reflected in the selection of the constituent elements of the portfolio by an investor while trading off risk and return. In this paper, after an initial level selection of for formulating a possible portfolio by using Perceptual Map (PM), we have applied DEA to calculate the efficiency of the stocks at the risk-return interface based on the market performance. In order to ascertain that the stock selection is logical and worthwhile, we further probe the fundamental performances over a time period of five consecutive financial years using the method of Multi-Criteria Decision Analysis (MCDA) framework based on the Complex Proportional Assessment (COPRAS) method, where, the criteria weights are calculated by using the entropy method. A consistency is visible in the yearly fundamental performances and a significant pattern with regard to the portfolio selection.

Keywords: Portfolio Selection, Stock Market, Perceptual Mapping, Data Envelopment Analysis (DEA), Complex Proportional Assessment (COPRAS).

I. INTRODUCTION

In the post-liberalization period, the Indian stock market (ISM) has witnessed a transformational growth, which substantially has accelerated by several reformatory initiatives taken by the Govt. of India (GOI) and rapid development at the Information Technology (IT) frontier. Because of its comparatively higher return with respect to the other conventional investment options like Fixed Deposits (FD), National Savings Certificates (NSC), and Public Provident Funds (PPF), ISM has been a lucrative investment avenue for the investors.

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However, in line with the famous propositions of renowned investment experts, one has to invest in multiple stocks instead of choosing a 'perfect' single stock because of two reasons: first, as stock market movement is dynamic and changing in nature and so as the behavior of the investors, the word 'perfect' is quite far-fetched; second, a bundle of stocks (preferably from the heterogeneous sectors) eases out the effect of the total risk. For rational capital investment in the stock market forming a portfolio is therefore quite imperative for negating the 'risk' factor while increasing the 'return' (Steinbach, 2001; Rubinstein, 2002). The underlying quest is how to allocate the total capital among the stocks forming the portfolio for balancing risk and return in line with the investors' financial perspectives and choices. In other words, the basic intention is to reduce the apparent controllable risk through effective diversification, which, in the domain of portfolio management, known as the diversifiable or unsystematic risk. Essentially, it forms the basic premise of the Modern Portfolio Theory (MPT) which rests on the principles of maximizing the return expected from a given portfolio while reducing portfolio risk (Fabozzi *et al*., 2002). MPT started with the seminal work by Markowitz (1952) addressed the issue of the portfolio selection within the framework of Mean-Variance (MV). While extending the theory, researchers postulated the use of Skewness and Kurtosis (Jaro and Na, 2005; Bhattacharyya *et al*., 2011; Bhattacharyya and Kar, 2011). In this regard, Briec *et al*. (2007) put forth the shortage function concept for measuring relative efficiencies with the objectives such as an increase in the mean return and skewness while decreasing the variances. Therefore, selection of the stocks for constructing a portfolio depends on multiple objectives which not only covers the return aspects, but also considers risk-based attributes and timing considerations. Further, the choice of portfolio selection is subject to the fulfillment of multiple objectives or criteria by trading off at the risk-return interface. Meanwhile, it is equally important to reflect on the fundamental performances of the constituent stocks at the organizational level, complementing the framework suggested by Markowitz (1952) and subsequently other extended frameworks (Jaro and Na, 2005). Quite understandably it provides the stability to the rational investment decision making by understanding the intrinsic value of the organizations (which assumes fair linkage with the stock level performance), efficiency and growth (Yoo and Shin, 2015). With this pretext, the paper is organized as follows. The next part looks into literature of same area of study. In the third part, we summarize the methodological framework used for the study. After this, we present the results and include subsequent discussions related to the findings. Lastly, the concluding section of the paper presents some remarks based on the result and highlights further scope for research.

II. LITERATURE REVIEW

DEA has been a widely used non-parametric approach for performance evaluation (Zohdi*et al.*, 2012) used for measuring efficiencies of the Decision-Making Units or DMUs in terms of efficiency scores which considers how much output is produced at a given consumption of the inputs. It has been considered by several researchers in evaluating the stocks based on the market performances as well as at the fundamental level. DEA intends to form an efficient frontier which points out maximum output (minimum input) at a specified level of input (output) as derived from the outputs and inputs which are observed in the DMUs. In turn, the DMUs which lie on and above the best practice or efficient frontier are accepted as 'efficient' units as compared to those which fall under the same (relatively efficient or non-efficient as decided by their relative distances from the efficient frontier) (Ferreira and Souza, 2015).The author (Morey and Morey, 1999) applied DEA in the context of the MV framework where they considered the variance as the input and expected return as the output. Abad *et al*. (2004) proposed a double-staged DEA framework based on the fundamental accounting parameters. Edirisinghe and Zhang (2007) put forth a generalized DEA framework to ascertain the financial strengths of the incumbent stocks in terms of predictive stock price return which is based on financial statements analysis. Zohdi *et al.* (2012) applied DEA in order to compare the stocks using financial ratios. However, though DEA is assessing the efficiencies of the DMUs which are comparable under a homogeneous operating environment, it cannot discriminate them in the orderly fashion precisely consider the preferences of the consumers, here, investors (Madlener *et al*., 2009). In other words, DEA classifies the DMUs into two broad categories: efficient and non-efficient. This paves the way to use the MCDM frameworks which enable the decision maker to rank the DMUs in tune with a number of criteria as provided by a decision maker. Over the years, researchers (Tsao, 2003; Xidonas *et al*., 2009, 2010; Tiryaki and Ahlatcioglu, 2009; Kiris and Ustun, 2010; Qu *et al*., 2011; Baležentis *et al*., 2012; Maikaew and Yanpirat, 2012; Shen *et al*., 2014; Poklepovic and Babic, 2014; Jamshidi and Ramshini, 2014; Dincer, 2015; Karmakar *et al*., 2018) have adopted and applied several outranking and attribute based MCDM approaches (using the crisp as well as the fuzzy frameworks) like TOPSIS, ELECTRE III, PROMETHEE, VIKOR, SAW, ARAS, AHP, MOORA, and MABAC. Some researchers (Tsao, 2006; Ballestero and Pla-Santamaria, 2003; Parra *et al*., 2001; Ehrgott *et al*., 2004; Ogryczak, 2000) also attempted to construct and solve the portfolio choice related decision through mathematical programs. While doing the performance-based assessment of the stocks for portfolio selection, researchers put emphasis on both the fundamental as well as return based parameters. Tsao (2003) considered ROE, EPS, Operational Income per Capital employed Net Income along with qualitative parameters like Service Quality. Ehrgott (2004) followed the utility-based assessment approach. Gupta *et al*. (2008) put forth a Semi-Absolute Deviation (SAD) framework considering both the aggressive and semi-aggressive standpoints. Xidonas *et al*. (2009) took into account three dimensions such as risk, return and market perception (i.e., acceptance) related to the fundamental and market return parameters. In line with this work, Ghaffari Nasab *et al*. (2011) contemplated on the stock performance using the parameters like liquidity, sales and market share. On the other hand, Ferreira *et al*. (2009) considered the economic indicators. With respect to these works, Kiris and Ustun (2010) attempted to view the whole agenda from the perspectives of investors, financial structure and sustainable business results. Baležentis *et al*. (2012) compared different sectors of Lithuania based on financial ratios while Pokle povic and Babic (2014)'s framework took into account the criteria like Beta, EPS, P/B ratio, P/S ratio, ROE, and ROA along with Volume, Standard Deviation, and Mean. Additionally, Deep *et al*. (2009) considered dividend where they took both the short run as well as long run return.

However, there are limited instances wherein efficiency assessment and subsequent rankings have been carried out, though, Mansouri *et al*. (2014) in the context of the Tehran stock exchange attempted to provide a DEA-TOPSIS based framework. Hence, in this study, we propose a combined framework wherein after identifying the efficient DMUs or stocks based on their relative market performances (using PM and DEA), we use MCDM framework for classifying them further considering the fundamental (i.e., accounting based) parameters.

III. METHODOLOGY

This study is in continuation to the contribution of the research work by Gupta *et al*. (2019) wherein the authors selected 53 companies listed in the NSE, India. The companies belong to various sectors, making it heterogeneous in nature and it spans within the NIFTY 100 list. Gupta *et al*. (2019) classified the stocks on the basis of monthly returns as derived from closing prices. Accordingly, they found three distinct clusters; High Stock Price (HSP), Mid Stock Price (MSP), and Low Stock Price (LSP), where 44 stocks' falls in 'LSP' cluster. In this study, we have considered those 44 stocks to begin with.

This study proposes a three-stage approach which first classifies the stocks using Perceptual Map (PM) for identifying the equities which fall under the 'low risk and high return' category. The study, then, applies DEA to measure their efficiency scores based on market return parameters wherein, the lower order as well as the higher moments is considered.

After obtaining the results, a proportionate based comparative ranking method (i.e., MCDM) such as COPRAS is applied taking into considerations four fundamental parameters at risk-return interface.

A. DATA

In this study, we have considered 44 heterogeneous stocks across different sectors enlisted with the (NSE), India as mentioned in the above section. The Table I represents initial list of stocks.

Table I. Initial list of stocks (Before drawing the PM)

List of Stocks		
Amara Raja Batteries Ltd.	Gail (India) Limited (GAIL)	United Breweries Holdings Ltd.
TVS Motor Company Limited	Reliance Industries Limited (RIL)	Jubilant Food Works Limited
Tata Motors Limited	NTPC Ltd.	Marico Ltd.
Bharat Forge Ltd.	Power Grid Corporation of India Ltd.	Colgate-Palmolive (India) Limited (COLPAL)
Mahindra and Mahindra Ltd	Tata Power Company Ltd.	Dabur India Ltd
Ashok Leyland Ltd.	Oil and Natural Gas Corporation Limited (ONGC)	Emami Ltd
Canara Bank	Bharat Petroleum Corporation Ltd. (BPCL)	Godrej Industries Limited
State Bank of India (SBI)	Reliance Infrastructure Ltd	KPIT Technologies Ltd
Bank of Baroda	Hindustan Petroleum Corporation Ltd. (HPCL)	HCL Technologies Ltd
HDFC Bank Ltd.	ITC Ltd.	Infosys Ltd
Yes Bank Ltd.	United Spirits Ltd (MCDOWELL-N)	Wipro Limited
IndusInd Bank	Tata Global Beverage Ltd.	Tech Mahindra Ltd
Punjab National Bank (PNB)	Hindustan Unilever Ltd. (HUL)	Tata Elxsi Limited
Federal Bank	Godrej Consumer Products Limited	MindTree Ltd
Indian Oil Corporation Limited (IOCL)	United Breweries Ltd. (UBL)	

The closing prices of those stocks have been collected from the database of the NSE, India over a period of 61 months during March 2013 to March 2018. Accordingly, respective return values are calculated (Guha *et al.*, 2016) using the following equation:

$$\text{Return } (R_s) = \text{Ln}\left(\frac{P_i}{P_{i-1}}\right).100\% \quad \textbf{(1)}$$

Where, P_i is the closing price of the current month and P_{i-1} is that of the immediately preceding month. Hence, we get total 60 return values for each stock and from the descriptive statistics of these stocks we get the standard deviation, maximum, minimum, skewness and kurtosis. The "Avgror" is calculated by taking the average of each stock 60 months return. This is shown in Table II.

Table II. Statistical description of these stocks

Sl	Stocks	Avgror	SD	Max	Min	Skew	Kurt
1	Amara Raja Batt	1.7%	7.7%	26.0%	-13.1%	38.0%	58.6%
2	TVS Motor	4.9%	11.8%	32.7%	-17.4%	37.0%	-29.3%
3	Tata Motors	0.6%	9.8%	25.5%	-16.6%	40.4%	-10.8%
4	Bharat Forge	3.1%	9.3%	22.1%	-25.2%	-12.1%	37.0%
5	M&M	0.9%	6.6%	15.8%	-15.2%	2.9%	-31.2%
6	Ashok Leyland	2.7%	12.7%	41.3%	-39.4%	31.8%	262.6%
7	Canara Bank	-0.4%	13.2%	37.3%	-30.1%	10.6%	34.3%
8	SBI	0.4%	9.5%	22.4%	-22.1%	17.7%	3.6%
9	BOB	-0.1%	10.8%	26.8%	-22.3%	20.3%	39.3%
10	HDFC Bank	1.8%	5.1%	13.8%	-9.3%	13.4%	-21.1%
11	Yes Bank	1.9%	12.2%	30.6%	-35.3%	-26.3%	119.6%
12	IndusInd Bank	2.3%	8.0%	23.3%	-18.8%	-1.0%	44.8%
13	PNB	-0.1%	14.1%	42.4%	-28.2%	44.3%	38.7%
14	Federal Bank	1.3%	11.2%	36.6%	-31.1%	23.0%	151.6%
15	IOC	1.5%	9.3%	31.2%	-19.7%	60.2%	103.0%
16	GAIL	1.1%	8.1%	20.3%	-18.9%	-3.0%	36.3%
17	RIL	1.2%	7.0%	18.6%	-15.7%	41.9%	22.5%
18	NTPC	0.2%	7.4%	32.2%	-17.6%	114.5%	484.5%
19	POWER GRID CORP	1.0%	5.8%	14.2%	-12.8%	13.4%	-24.3%
20	TATA POWER	-0.1%	8.5%	28.4%	-21.1%	39.6%	122.2%
21	ONGC	-0.3%	8.2%	23.7%	-15.4%	21.1%	-16.5%
22	BPCL	2.3%	9.1%	19.6%	-17.1%	-18.2%	-55.4%
23	Rel Infra	0.1%	12.0%	30.6%	-25.6%	21.0%	-2.0%

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24	Hind Petro (HPCL)	3.0%	10.6%	24.2%	-23.2%	-15.6%	-17.3%
25	ITC	0.4%	5.3%	11.5%	-12.6%	-24.9%	-7.1%
26	MCDOWELL N	-0.7%	17.0%	52.1%	-49.3%	17.8%	148.8%
27	TATA GLOBAL	1.3%	9.3%	23.5%	-20.0%	-15.2%	-14.9%
28	HUL	1.8%	6.1%	22.3%	-6.8%	109.2%	234.5%
29	GODREJ CP	1.7%	6.3%	16.4%	-12.9%	0.9%	15.9%
30	UBL	0.7%	8.8%	22.4%	-21.2%	-44.2%	124.4%
31	UB (H) L	-3.2%	19.6%	42.9%	-51.7%	-26.2%	49.9%
32	JUBILANT FOODWORKS	0.6%	11.5%	33.1%	-24.6%	39.5%	11.8%
33	MARICO	1.8%	5.5%	17.9%	-12.8%	5.0%	80.6%
34	COLPAL	0.8%	5.6%	17.0%	-13.4%	-3.9%	159.1%
35	DABUR	1.6%	4.8%	11.5%	-10.0%	-22.3%	-40.3%
36	EMAMI LTD	2.1%	7.8%	18.7%	-15.3%	18.7%	9.6%
37	GODREJ IND	1.2%	8.4%	21.4%	-18.4%	14.0%	-2.3%
38	KPITTECH	0.8%	12.7%	24.8%	-58.4%	-185.4%	746.2%
39	HCLTECH	1.6%	6.8%	18.9%	-12.5%	10.1%	5.7%
40	INFOSYS	0.7%	7.8%	18.5%	-25.7%	-66.8%	135.7%
41	Wipro	0.7%	7.2%	22.7%	-22.7%	-11.6%	225.5%
42	TECH MAHINDRA	1.2%	7.8%	16.2%	-18.8%	-34.4%	-35.1%
43	TATA ELXSI	3.7%	12.6%	37.6%	-20.6%	111.0%	106.7%
44	MINDTREE	1.9%	9.4%	17.6%	-21.8%	-45.6%	-51.4%

We apply perceptual map (PM) where the origin of axes is shifted to the point having Combined Mean (CAR) and combined Standard Deviation (CSD) values. Hence, the results construct four new quadrants representing "(Low SD, Low Mean), (Low SD, High Mean) (High Mean, High SD), (High SD, Low Mean)", shown in the figure 1.

Combined AVROR (CAR) = Average (AVROR) **(2)**

Combined SD (CSD) = $\frac{\sqrt{\Sigma\left(d_j^2+SD_j^2\right)}}{k}$; where, d_j= Average return for j^{th} Stocks – CAR; j = 1,2,…k **(3)**

The PM classifies the stocks and accordingly we get total 18 stocks fall under the category 'low risk and high return' (Table III).

Table III. List of the selected 18 companies (i.e., stocks) using PM

Company (Stock)	Code
Amara Raja Batteries Ltd.	B1
Bharat Forge Ltd.	B2
HDFC Bank	B3
IndusInd Bank	B4
Indian Oil Corporation Limited (IOCL)	B5
Gail (India) Limited (GAIL)	B6
Reliance Industries Limited (RIL)	B7
Bharat Petroleum Corporation Ltd. (BPCL)	B8
Tata Global Beverage Ltd.	B9
Hindustan Unilever Ltd. (HUL)	B10
Godrej Consumer Products Limited	B11
Marico Ltd.	B12
Dabur India Ltd	B13
Emami Ltd	B14
Godrej Industries Limited	B15
HCL Technologies Ltd	B16
Tech Mahindra Ltd	B17
MindTree Ltd	B18

In the next phase, we have used DEA to calculate the efficiency-based scores of the stocks (total 18 numbers as obtained from the PM) based on four parameters: Average Return (Avgror), Standard Deviation (SD), Skewness (Skew) and Kurtosis (Kurt). In the present study, the normalized values of all these parameters are used. Average return, the first order moment about the origin signifies the mean return generated by the stock over the period of study while SD (second order moment about the mean) represents the variability in the return (i.e., the scattered nature of the return distribution). However, several researchers (Samuelson, 1970; Konno and Suzuki, 1995; Konno *et al.*, 1993; Stone, 1973; Chunhachinda *et al.*, 1997; Bhattacharyya *et al.*, 2011; Beardsley *et al.*, 2012) have pointed out that the higher order moments are of significance in deciding the performance of the stocks. Hence, we also include them (Skewness and Kurtosis) in our study. Skewness (third order moment about the mean) signifies the possibility of a higher pay-off at the given values of mean and variance while Kurtosis (fourth order moment about the mean) is an indicator of the peakedness which essentially represents the future price behavior adjusted by the volatility.

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In our study we take Average Return (Avgror) and Standard Deviation (SD) as Input and Skewness (Skew) and Kurtosis (Kurt) as Output.

The underlying aim is to formulate an optimal portfolio from the perspective of the investor which ensures maximum possible return under varying risk levels or minimum affordable risk with varying expected return values (Banihashemi and Sanei, 2015). In order to rank these stocks using COPRAS we consider four fundamental criteria such as: Return on Assets (ROA), Return on Equity (ROE), Asset Turnover (AT), and Financial Leverage (FL). For calculation purposes necessary data are obtained from the database of CMIE Prowess IQ. The value of ROA (net income /total assets) signifies the capacity of the company to make profits (i.e., return) by using its assets. On the other hand, the value of ROE (net income/ shareholders' equity) is interpreted as the ability to report profit (i.e., return) by the organization on account of the investment made by the investors (Heikal *et al*., 2014). AT (Ratio of total sales and total assets) is an indicator of the ability of the organizations to generate sales out of their assets. In other words, it specifies the competitive capabilities of the management (Altman, 1968). Higher values of these ratios indicate healthy position of the company. Hence, they are beneficial (B) criteria from the perspective of the investors. Meanwhile, FL indicates firm's liability in relation to its assets, i.e., default risk in the near future (Rajan and Zingales, 1995). Therefore, it is non-beneficial (NB) in nature.

B. PERCEPTUAL MAP (PM)

Perceptual Mapping is a diagrammatic technique to display the perception of investor with respect to mean (Return) and SD (Risk). In our study, PM typically displayed the position of mean and SD with respect to combined mean and combined SD. Here, combined mean and combined SD shifted its axis from the origin and classify the map into four quadrant which are High Mean High SD, High Mean Low SD , Low Mean High SD and Low Mean Low SD.

C. DEA (DATA ENVELOPMENT ANALYSIS)

In operations research and economics study, the data envelopment analysis (DEA) is a nonparametric method to estimate the production frontiers. It is utilized to exactly quantify beneficial effectiveness of basic leadership units (DMUs). In the study works of Charnes *et al*. (1978) and Banker *et al*. (1989), the calculations for an input-oriented DEA are given as under:

Constant Return to Scale (CRS) model:

$\min \theta$

Subject to

$\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{it}$ $i = 1,2,\dots,m$; Input Constraint **(4)**

$\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{rt}$ $r = 1,2,\dots,s$; Output Constraint **(5)**

Where, $\lambda_j \ge 0 \;\forall\, i,j,r$

Variable Return to Scale (VRS) model:

$\min \theta$

Subject to

$\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{it}$ $i = 1,2,\dots,m$; Input Constraint **(6)**

$\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{rt}$ $r = 1,2,\dots,s$; Output Constraint **(7)**

Where, $\sum_{j=1}^{n}\lambda_j = 1$; $\lambda_j \ge 0 \;\forall\, i,j,r$

In case if two or more DMUs stand efficient (i.e. θ = 1 or 100%) then the Super-efficiency value is calculated in order to discriminate them. For VRS the super efficiency is given by:

$\min \theta$

Subject to

$\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{it}$ $i = 1,2,\dots,m$; Input Constraint **(8)**

$\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{rt}$ $r = 1,2,\dots,s$; Output Constraint **(9)**

Where, $\sum_{j=1}^{n}\lambda_j = 1$; $\lambda_j \ge 0 \;\forall\, i,j,r\,;\, j \neq t$

D. ENTROPY METHOD

This is an objective method for calculating the criteria weights based on the relative information storage, i.e., based on the level of disorder (Shannon, 1948). Higher entropy value signifies greater amount of information contained by the respective criterion. In line with the steps as described by Li *et al*. (2011), the said method can be explained as:

Let, $X = [x_{ij}]_{m\times n}$ is the decision matrix where i= 1,2,3….m is the number of alternatives and j= 1,2,3… n is the number of criteria. Hence, x_{ij} : j^{th} criterion value for the alternative ith

Step1: Standardization of the Criteria (for avoiding criteria influence on the alternatives)

Suppose, $R = [r_{ij}]_{m\times n}$ is the standardized matrix.

Where

$r_{ij} = \frac{x_{ij}}{\max_j x_{ij}}, i = 1,2,\dots.m; j = 1,2,\dots n$ (For beneficial criteria) **(10)**

$$r_{ij} = \frac{\min_j x_{ij}}{x_{ij}}, i = 1,2,\dots.m; j = 1,2,\dots n$$

(For non-beneficial criteria)

Step 2: Entropy calculation

Entropy of the j^{th} criterion is given by:

$H_j = -\frac{\sum_{i=1}^{m} f_{ij}\ \ln(f_{ij})}{\ln(m)}, i = 1,2,\dots m; j = 1,2,..n$ **(11)**

Where,

$f_{ij} = \frac{r_{ij}}{\sum_i^m r_{ij}}, i = 1,2,\dots m; j = 1,2,\dots n$ **(12)**

Step 3: Derivation of the weight

The weight (based on entropy value) of the j^{th} criterion is obtained by:

$w_j = \frac{1-H_j}{n-\sum_{j=1}^{n} H_j}$, where $\sum_{j=1}^{n} w_j = 1$ **(13)**

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E. COPRAS (COMPLEX PROPORTIONAL ASSESSMENT)

The COPRAS method considers the direct and proportional dependencies of the conflicting criteria (maximizing or minimizing in nature) on the alternatives for generating evaluation results (Zavadskas *et al.*, 2009; Chatterjee and Chakraborty, 2014). There has been a plethora of research contributions using COPRAS as an MCDA aid in solving complex decision-making problems (Vilutiene and Zavadskas, 2003; Kaklauskas *et al.*, 2005; Viteikiene and Zavadskas, 2007; Madić*et al.*, 2014; Kundakcı and Işık, 2016). The steps in evaluating the significance and priority of the alternatives using COPRAS method are as under:

Step 1: Construct the normalized decision matrix

There are a number of approaches available for normalization (Ginevicius, 2007; Zavadskas et. al., 2008). In this method, the normalized value of the i^th^ alternative for j^th^ criterion is given by:

$$\widetilde{d_{ij}} = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}} \quad (14)$$

i = 1,2…..m (number of alternatives); j= 1, 2, 3… n (number of criteria)

Step 2: Calculation of the sums of the weighted normalized criteria

The underlying objective of this method is to optimize both the maximizing and minimizing criteria, but in two directions: ideal and anti-ideal. Necessary calculations for maximizing and minimizing criteria are given as:

$$S_{+i} = \sum_{j=1}^{k} \widetilde{d_{ij}} \cdot q_j \quad (15)$$

$$S_{-i} = \sum_{j=k+1}^{n} \widetilde{d_{ij}} \cdot q_j \quad (16)$$

Here, k is the number of maximizing (i.e., beneficial) criteria and q_j is the significance of the j^{th} criterion.

Step 3: Calculation of the relative weights of the alternatives

The relative weight for any alternative (i^{th}) is given as:

$$Q_i = S_{+i} + \frac{\min_i S_{-i} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{\min_i S_{-i}}{S_{-i}}} \quad (17)$$

Or (in simpler form)

$$Q_i = S_{+i} + \frac{\sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \left(\frac{1}{S_{-i}}\right)} \quad (18)$$

The utility for each alternative is given by:

$$U_i = \frac{Q_i}{Q_{i\,max}} \cdot 100\% \quad (19)$$

Decision rule: The alternative which secures highest utility will be ranked first and so on.

For analysis purpose in our study we use Microsoft Excel (office 10 version) and IBM SPSS (version 20) software tools.

IV. RESULTS AND ANALYSIS

Fig 1 exhibits the PM which classifies the stocks based on return (high or low) and risk (high or low) dimensions. Accordingly, we get the 18 stocks as mentioned in the table III. We then conduct DEA. Table IV summarizes the findings of DEA. It is evident from the results of the DEA that B10 (i.e. HUL) and B5 (i.e. IOCL) both achieves 100 percent efficiency and B7 (i.e. RIL) comes in the top 3 list. On the other hand, B13 (i.e. Dabur), B17 (i.e. Tech Mahindra) and B18 (i.e. MindTree) belong to bottom 3 lists.

However, looking into their price movements during the study period and considering their relative business value, it is not so comprehensive in nature, though; DEA provides a considerably fair idea about their relative positions based on return distribution-based parameters.

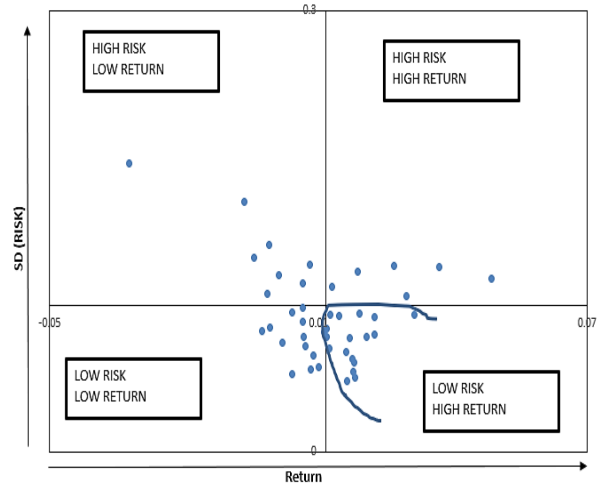

Fig 1. Perceptual Map (for 44 stocks – initial list)

Table IV. DEA Result

DMUs	Output (DEA)		Input (DEA)		Measurement			Rank
	Nor_Kurt	Nor_Skew	Nor_Avgror	Nor_SD	CRS	VRS	Efficiency	
B1	0.249	0.029	0.831	0.200	0.249	0.926	0.268	12
B2	0.068	0.109	1.000	0.262	0.223	0.754	0.296	8
B3	0.224	0.038	0.839	0.156	0.249	0.994	0.25	13
B4	0.151	0.112	0.916	0.228	0.256	0.834	0.307	7
B5	**0.337**	**1.000**	**0.774**	**1.000**	**1**	**1**	**1**	**1**
B6	0.203	0.109	0.718	0.230	0.286	1	0.286	9
B7	0.446	0.097	0.784	0.202	0.471	0.979	0.481	3
B8	0.110	0.006	0.863	0.258	0.106	0.846	0.125	15
B9	0.166	0.045	0.759	0.256	0.181	0.946	0.191	14
B10	**1.000**	**0.369**	**0.828**	**0.173**	**1**	**1**	**1**	**1**
B11	0.158	0.100	0.838	0.185	0.261	0.932	0.281	10
B12	0.223	0.149	0.842	0.165	0.425	0.96	0.442	4
B13	0.036	0.036	0.793	0.151	0.113	1	0.113	16
B14	0.246	0.070	0.810	0.234	0.252	0.912	0.276	11
B15	0.306	0.073	0.745	0.235	0.34	0.983	0.346	5

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B16	0.301	0.078	0.797	0.198	0.313	0.963	0.326	6
B17	0.083	0.035	0.794	0.232	0.089	0.923	0.097	17
B18	0.036	0.017	0.862	0.271	0.037	0.838	0.044	18

In order to complement our understanding, we then move to analyzing the fundamental performances (year wise) of the stocks under consideration during the study period (i.e., April 2013 to March 2018). In order to do so, we apply the COPRAS method. Table VI provides the year to year ranking of the stocks (18 numbers) based on the fundamental criteria as mentioned in the above, while table V. presents the criteria weight as obtained from the Entropy method.

Table V. Criteria Weights (From Entropy Method)

Criterion	**C1**	**C2**	**C3**	**C4**
H-Value	0.925056	0.945288	0.938938	0.964535
Weights	0.331344	0.241893	0.269967	0.156797

Table VI. COPRAS Based Ranking Of The Stocks (Yearly Basis)

DMUs	**FR 2013-14**		**FR 2014-15**		**FR 2015-16**		**FR 2016-17**		**FR 2017-18**	
	U- Value	**Rank**	**U- Value**	**Rank**	**U- Value**	**Rank**	**U- Value**	**Rank**	**U- Value**	**Rank**
B1	56.412	5	56.434	6	60.853	5	53.524	4	49.487	6
B2	27.556	13	34.123	11	31.154	12	30.877	12	33.101	13
B3	9.470	18	9.771	18	10.066	18	10.534	18	11.503	18
B4	9.930	17	10.547	17	11.080	17	10.783	17	11.611	17
B5	27.811	12	25.044	12	31.424	11	38.328	11	39.907	11
B6	29.802	11	23.358	13	21.560	15	26.545	13	33.783	12
B7	27.152	14	22.987	14	21.660	14	20.285	15	21.912	15
B8	42.850	9	42.006	9	48.012	8	47.598	7	47.552	7
B9	24.932	15	19.887	15	23.477	13	23.440	14	25.309	14
B10	**100**	**1**	**100**	**1**	**100**	**1**	**100**	**1**	**100**	**1**
B11	33.151	10	34.689	10	40.109	10	38.365	10	41.375	9
B12	45.411	8	58.920	5	68.877	2	69.662	2	67.137	2
B13	53.305	7	53.460	7	57.442	6	52.505	5	50.706	5
B14	76.229	2	75.869	2	50.586	7	43.696	8	40.822	10
B15	17.705	16	18.532	16	20.319	16	15.257	16	16.646	16
B16	54.071	6	62.032	3	61.712	3	54.670	3	55.907	3
B17	63.125	3	45.090	8	47.790	9	42.341	9	46.177	8
B18	62	4	59.6	4	61.2	4	48.7	6	55.5	4

	.713		28		88		03		65	

It is now comprehensibly evident that B10(HUL) stands out the top performer based on fundamental performance criteria during the entire study period. The same holds good for B15 (Godrej Industries Ltd), B4 (IndusInd Bank), and B3(HDFC Bank) as they consistently hold the last three positions. However, there are some interesting observations. First, it is only HUL that could secure the top position both in terms of the market performance as well as the fundamental one. Otherwise, there is no significant consistency between the market performance (as revealed through the DEA results) and fundamental criteria-based rankings (as obtained through COPRAS). There could be many reasons. Perhaps, as during the study period some sectors (e.g., Banks) underwent major reformatory moves as compared to the sectors like FMCG, there is an inconsistency between the performances of the stocks at two levels: market and account. Second, the performances of the stocks at the fundamental level are consistent in nature and the consistency level is statistically highly significant. This we can infer from the results of the Spearman's Rank Correlation test (Table VII). Under this method, the correlation coefficient is given by:

$$\rho = 1 - \frac{6\sum d_i^2}{n\,(n^2-1)} \qquad \textbf{(20)}$$

Here, d_i is the difference in the rankings for the alternative i, as generated by different MCDM methods.

Table VII. Rank Correlation Results

	FR_2013_14	FR_2014_15	FR_2015_16	FR_2016_17	FR_2017_18
FR_2013_14	1.000				
FR_2014_15	.946**	1.000			
FR_2015_16	.866**	.950**	1.000		
FR_2016_17	.858**	.932**	.986**	1.000	
FR_2017_18	.847**	.907**	.973**	.983**	1.000
**. Correlation is significant at the 0.01 level (2-tailed).					

Here, FR_2013_14 indicates the ranking of the alternatives (i.e., DMUs) based on the fundamental parameters for the financial year 2013-14.

V. CONCLUSION

In the present study, a holistic approach has been adopted for understanding the performances of the stocks which is provided by integrating the market performance with the fundamental counterpart in an MCDM framework using a three stage model (Perceptual Map – DEA – COPRAS) and we found that **B10(HUL)** stands out the top performer based market performance and fundamental performance.

The study aims to bolster the individual investors to invest in the stock which has low stock price and choose their portfolio on the basis of high return- low risk.

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VI. FUTURE SCOPE

This study provokes some interesting further research agenda. One can study the detailed organizational level performance study. As a matter of fact, the sample considered is rather small in nature and poses a challenge to a detailed study. Thus, it might be appropriate to consider this as a 'pilot study' which needs further exploration. But individual conservative investors are likely to profit by the outcome of the study in their portfolio construction.

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