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PORTFOLIO OPTIMIZATION USING DATA ENVELOPMENT ANALYSIS & SHARPE'S METHOD

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ABSTRACT

Due to the advancement of Information Technology it has been easier for investors to invest valuable money in portfolios. There has been availability of tools & data all the time to predict the market in decision-making, for which some models have been developed. With the rigorous research in this attractive topic some mathematical models have been developed & some models from other industries have been considered. Models like Sharpe, Genetic Algorithm, and Monte-Carlo are very helpful in investment decision making. DEA model, originated from production industry, helps in selecting securities for portfolio. In this paper we have exquisitely tried to find out the best method for selection of efficient securities using historical data of BSE-30 industries & compared DEA, Sharpe's model with Market, which gives some exciting results for future investment.

KEYWORDS

Portfolio Allocation, Stocks Market, Data Envelopment Analysis, Sharpe's method.

INTRODUCTION

The portfolio selection problem with one investment period is a particular case of the general problem of choosing between random variables when larger outcomes are preferred. There is, therefore, a need for models that make a choice between random variables (models for preference). Basically, there are three main types of such models: mean-risk models, expected utility maximization, and stochastic dominance models. Mean-risk models are convenient from a computational point of view, but in many cases, depending on the risk measure that is used, they may lack a rational, theoretical basis for making a choice. Thus, the validity of the results provided is often questionable. Expected utility maximization is usually difficult to put into practice since the choice of a suitable utility function is somewhat subjective. Stochastic model is particularly important in investment problems since it describes the preference of rational and risk-averse decision-makers.

The mean-variance portfolio model rely fundamentally on approximate description of the probability distribution function of asset returns in terms of Gaussian functions, which is necessary in order for the two models to exactly match the expected utility approach. The mean-variance description is thus at the basis of Markowitz portfolio theory and of the Capital Asset Pricing Model (CAPM). While the variance (or volatility) of portfolio returns provides the simplest way to quantify its fluctuations, it offers only a limited understanding of incurred risks (in terms of fluctuations), because the empirical distributions of returns have fat tails, and the dependencies between assets are only imperfectly accounted by the covariance matrix. Absolute central moments provide extensions of the variance measure of risks, because they satisfy the basic requirement for consistent measures of risks, including in most combinations. The weights can be interpreted in terms of the portfolio manager's aversion to large fluctuations. This approach provides a natural extension of the multi-moment investment optimization methodology, which is based on a linear expansion of the utility function of the economic agent.

LITERATURE REVIEW

Markowitz (1952) was the first to model the important trade-off between risk and return in portfolio selection as an optimization problem. He suggested choosing an asset mix so that the portfolio variance is minimal for any target level of expected return. 60 years after Markowitz's seminal idea, despite substantial contributions to portfolio risk management theory, important practical issues remain unresolved. Portfolio allocation decisions are frequently made on the basis of solutions of optimization algorithms that treat parameters in the models such as means, variances, and co-variances of returns, as given. These parameters, however, are estimated through error-prone procedures, e.g., statistical modeling or subjective evaluation. Since optimization results are very sensitive to perturbations in parameter values, the computed optimal portfolio strategies are unreliable. In the case of standard mean-variance portfolio optimization, practitioners frequently resolve the issue by sampling the mean returns and the covariance matrix from a confidence interval around a nominal set of parameters, and then aggregating the portfolios obtained by solving a Markowitz problem for each sample. Unfortunately, this technique does not provide any guarantees, and may become quite inefficient as the number of assets grows [3]. It is a well-documented fact in the investment management literature that mean-variance optimizers are very sensitive to small variations in expected returns. Slightly different expected return vectors can lead to drastically different portfolios. The seemingly unexplainable changes in asset weights due to small perturbations in expected returns are not the only pitfall of classical mean-variance optimization. Because of the error-maximization effect, it is typically the case that the expected return is significantly overestimated [6].

Full-scale optimization relies on sophisticated search algorithms to identify the optimal portfolio given any set of return distributions and based on any description of investor preferences. Full-scale optimization yields the truly optimal portfolio in sample, whereas the mean–variance solution is an approximation to the in-sample truth. Both approaches to portfolio formation, suffer from estimation error. Mean–variance analysis requires investors to estimate the means and variances of all assets and the co variances of all asset pairs. To the extent the out-of-sample experience of these parameters departs from the in-sample parameter values, the mean–variance approximation will be even less accurate. Full-scale optimization requires investors to estimate the entire multivariate return distribution. To the extent it varies from the in-sample distribution, full-scale optimization will also yield sub-optimal results out of sample [1].

Timothy Adler & Mark Kritzman [1] employed a bootstrapping procedure to compare the estimation error of full-scale optimization to the combined approximation and estimation error of mean–variance analysis. They found that, to a significant degree, the in-sample superiority of full-scale optimization prevails out of sample. They suggested that if it is optimized among assets those are likely to have persistent non-normal higher moments and it should be cared about thresholds or view gains and losses differently, it should be considered full-scale optimization as an alternative to mean-variance analysis.

The concept of stochastic dominance or stochastic ordering of random variables was inspired by earlier work in the theory of majorization that is, ordering. It has been used since the early 1950’s, in fields such as statistics. In economics, stochastic dominance was introduced in the 1960’s; Quirk and Saposnik considered the first order stochastic dominance relation and demonstrated the connection to utility functions. Second order stochastic dominance was brought to economics by Hadar and Russel. Diana Roman, Ken Darby-Dowman, Gautam Mitra [2] presented a model for portfolio selection, which provides a meaningful solution, corresponding to observed economic behavior, and at the same time is practical from a computational point of view. The solution is meaningful in the sense that the selected portfolio is non-dominated with respect to second order stochastic dominance (SSD) and therefore optimal for every rational and risk averse investor. In addition, this portfolio has a return distribution close to a user-specified target distribution. Thus, this return distribution can be shaped and crafted to a desirable form, to the extent that is achievable. In the case of mean-risk models consistent with SSD, the only criterion for selecting a specific portfolio is a desired trade-off between mean return & risk.

Capital Asset Pricing Model (CAPM) is a linear general equilibrium model that relates required rate of return with security's beta or systematic risk. It assumes perfect market, expected returns and standard deviation parameters, homogenous expectations, unlimited borrowing and lending at the riskless rate of interest, no transaction cost and taxes. All CAPM equilibrium models use mean-variance analysis including that of Elton and Gruber which indicated that CAPM under conditions of uncertain inflation can be derived by assuming a utility function defined in terms of mean-variance of real returns. Arbitrage Pricing Model is the alternative asset-pricing model introduced by Ross [4]. It is a different approach to asset pricing based considering the law of one price; it states that two assets that are in the same risk class cannot sell at different prices because arbitraging will set in. The strong assumptions made about utility theory for CAPM are not necessary and the description of equilibrium is more general, as influences can be beyond mean-variance. It only assumes perfect competition, Homogenous expectations, and risk averse investors. It assumes that returns on securities are influenced not just by the market index but other macroeconomic factors also [4].

Optimization of long-short portfolios through the use of fast algorithms takes advantage of models of covariance to simplify the equations that determine optimality. Fast algorithms exist for widely applied factor and scenario analysis for long-only portfolios. To allow their use in factor and scenario analysis for long-short portfolios, the concept of "trim-ability" is introduced. The conclusion is that the same fast algorithms that were designed for long-only portfolios can be used, virtually unchanged, for long-short portfolio optimization provided that portfolio is trim-able, which usually holds in practice [5]. Realistic models of long-short portfolio restrictions can be written as systems of linear equality or inequality constraints.

Given today’s volatile global investment climate, the increasing number of private investors and managed funds, and the growing financial services industry, investment performance appraisal is of paramount importance. Investors, of course, have always been eager to assess the performance of their managed portfolios. In early days, performance was evaluated by comparing the total return of a managed portfolio with that of a randomly chosen unmanaged portfolio (Modigliani and Modigliani, 1997). Later, the concept of an unmanaged ‘market’ or a capitalization-weighted portfolio comprising the entire market was introduced so that managed portfolio performance could be evaluated and compared against the market portfolio as a benchmark.

It is well-known that the return earned by a portfolio alone is not an accurate measure of its performance. Further, it is well-established that higher expected returns are associated with higher levels of risk. The downside to this is the possibility of considerable return losses due to market uncertainty. In short, there is a trade-off between risk and return. Investors are generally risk aversive. Therefore, for any risk associated with their investment, investors expect compensation or a risk premium. Consequently, several basic performance appraisal methods emerged in the late 1960s. With the rapid growth and globalization of financial sectors, the financial services industries responded with new relative performance measures that have now become very popular and are widely used by private and institutional investors. However, there is no consensus in the literature as to what a suitable measure of risk is, and consequently, as to what is a suitable measure for evaluating risk-adjusted performance.

According to the mean-variance analysis which is the basic of Modern Portfolio Theory, in order to make a decision, the investor should calculate the estimated return, standard deviations of all stocks and most importantly the covariance between these stocks. In this method, the number of data to be calculated would increase exponentially with the increase in the number of stocks. This would be complicated. Then there several models are improved to answer the question ‘is it possible to allocate successful portfolio using with less input and information?’[8]

DATA ENVELOPMENT ANALYSIS

Data envelopment analysis (DEA) is a new technique developed in operations research and management science over the last two decades for measuring productive efficiency. This is a nonparametric technique based only on the observed input output data of firms or decision making units (DMUs) and it does not require any data on the input and output prices. Due to this flexible feature it has been widely applied to the public sector enterprises [9]. Data envelopment analysis is receiving increasing importance as a tool for evaluating and improving the performance of manufacturing and service operations. It has been extensively applied in performance evaluation and benchmarking of schools, hospitals, bank branches, production plants, etc. [10]. DEA is commonly used to evaluate the relative efficiency of a number of producers. A typical statistical approach is characterized as a central tendency approach and it evaluates producers relative to an average producer. In contrast, DEA is an extreme point method and compares each producer with only the "best" producers [8]. The main shortcoming in the common measures of risk-adjusted return is their inability to incorporate the costs incurred in generating the returns. In the late 1990s, several studies attempted to measure managed portfolio performance by considering the return adjusted for both risk and cost, using a non-parametric methodology of production frontier estimation commonly known as data envelopment analysis (DEA) [11].

DEA is a multi-factor productivity analysis model for measuring the relative efficiencies of a homogenous set of decision making units (DMUs). The efficiency score in the presence of multiple input and output factors is defined as:

Efficiency = (weighted sum of outputs)/ (weighted sum of inputs)

Assuming that there are n DMUs, each with m inputs and s outputs, the relative efficiency score of a test DMU p is obtained by solving the following model.

$$\max \quad h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}}$$

$$\text{subject to:} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1,\ j = 1,\ 2,\dots,\ n$$

$$u_r,\ v_i \geq \varepsilon \text{ with } r = 1,\ 2,\dots,\ s;\ i = 1,\ 2,\ \dots,\ m$$

where: k is the DMU under evaluation, y_{rj} is the amount of output r of the DMU_j ; x_{ij} is the amount of input i of the DMU_j ; u and v are the weights assigned respectively to output r and input i; ε is an infinitesimal positive number ,imposed to assure that no input or output is being ignored during the optimization.

The fractional program can be converted to a linear program.

$$\max \quad h_k = \sum_{r=1}^{s} u_r y_{rk}$$

$$\text{subject to:} \quad \sum_{i=1}^{m} v_i x_{ik} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} \leq \sum_{i=1}^{m} v_i x_{ij},\ j = 1,\ 2,\ \dots,\ n$$

$$u_r,\ v_i \geq \varepsilon \text{ with } r = 1,\ 2,\dots,\ s;\ i = 1,\ 2,\dots,\ m$$

The above problem is run n times in identifying the relative efficiency scores of all the DMUs. Each DMU selects input and output weights that maximize its efficiency score. In general, a DMU is considered to be efficient if it obtains a score of a1 and a score of less than 1 implies that it is inefficient [10].

SHARPE'S METHOD

Let us recall first that the purpose of returns-based style analysis is to determine a manager's effective asset mix with respect to a set of asset classes. This means that we are trying to determine the manager's exposure to changes in the values of the asset classes. To this end, a set of style coefficients is calculated, one for each asset class. Each style coefficient represents the exposure of the manager to the respective asset class.

Let M be the manager return series and A1, A2, A3, A4 the return series of the chosen asset classes, i.e., the style indices. Sharpe's method determines the style attribution coefficients c1, c2, c3, c4 in such a way that the variance of the series

M - (c1A1 + c2A2+ c3A3+ c4A4)

becomes minimal. Needless to say, one could use any number of asset classes; the number four is chosen here as an example. Referring to the expression c1A1 + c2A2+c3A3+ c4A4 (i.e., the weighted composite of the asset classes) as the "style benchmark," this can be rephrased as follows:

The style attribution coefficients are determined in such a way that the variance of the excess return of the manager over the style benchmark becomes minimal.

If one translates the above into a mathematical algorithm, then the problem boils down to performing a certain quadratic optimization. It is not necessary go into any of the gory details here; the italicized statement above is a complete and rigorous description of the mathematics of returns-based style analysis.

Sharpe's original paper constrains the analysis by requiring that all coefficients be between 0 and 1, and that the coefficients add up to 1. One may relax some or all of these constraints. The discussion below is not affected by the type of constraints that are used.

There is just one more mathematical aspect that is worth discussing, and that is the question of the uniqueness of the solution. What if there were two entirely different sets of style coefficients, resulting in two entirely different style benchmarks, and the excess return of the manager over these two different style benchmarks were the same minimal value? Which one of the two sets of style coefficients would Style advisor choose?

The answer is that such a situation can never occur. It can be proved mathematically that there always exists exactly one set of style coefficients such that the excess return of the manager over the corresponding style benchmark is minimal. This proof is far beyond the scope of this article. The following high-level summary of the proof is for the reader with a graduate level mathematics background: Minimizing the variance of excess return of the manager over the style benchmark amounts to finding the shortest distance between a point and a convex set in a certain Euclidean space; it is true in every Euclidean space that this distance is assumed at exactly one point on the convex set.

RETURNS-BASED STYLE ANALYSIS VS. MULTIVARIATE REGRESSION

William F. Sharpe's method of returns-based style analysis is substantially different from classical multivariate regression analysis. While there is a strong mathematical connection between Sharpe's method and classical multivariate constrained regression, the two are clearly different. Sharpe's method employs quadratic optimization to minimize the variance of the excess return of the manager over a linear combination of the asset classes. Regression analysis, by contrast, seeks to minimize the sum of the squares of the difference between the manager and a linear combination of the asset classes. Moreover, the linear combination of the asset classes used in regression analysis usually includes a constant alpha, which is not present in Sharpe's method.

Classical multivariate regression analysis determines a constant α and coefficients r1, r2, r3, r4 in such a way that the sum of the squares of the series

M - (α + r1A1 + r2A2+ r3A3+ r4A4)

is minimized. If the regression is performed with alpha constrained to 0, then the expression above becomes the same that was used in Sharpe's method, but the quantity that gets minimized is different: in Sharpe's method, it is the variance, while in regression analysis; it is the sum of the squares.

This shows that Sharpe's method and multivariate regression are simply two different methods with different intents. However, there is a mathematical connection between the two. The coefficients that minimize the variance of the expression

M - (c1A1 + c2A2+ c3A3+ c4A4)

Happen to be the same ones that minimize the sum of the squares of the expression

M - (α + r1A1 + r2A2+ r3A3+ r4A4)

Therefore, the following is true:

Performing a returns-based style analysis according to William F. Sharpe's method is equivalent to performing a classical multivariate linear regression with unconstrained alpha and then "dropping the alpha," i.e., considering only the regression coefficients r1, r2, r3, r4. [12].

It should be clear that this connection between Sharpe's method and classical regression analysis is rather accidental. The original intent of the two methods is different: minimizing variance is different from minimizing the sum of the squares. It just so happens that under certain circumstances (unconstrained alpha), the coefficients come out to be the same.

WORK DONE & METHODOLOGIES

Terminologies

Earning Per Share (EPS): Earnings per share (EPS) are the earnings returned on the initial investment amount. The last quarter data has been taken for the quarter for which portfolio is being constructed.

Price to Earnings Ratio (P/E Ratio): The P/E ratio (price-to-earnings ratio) of a stock (also called its "P/E", "PER", "earnings multiple," or simply "multiple") is a measure of the price paid for a share relative to the annual income or profit earned by the firm per share. The last quarter data has been taken for the quarter for which portfolio is being constructed.

Risk (Standard Deviation): Risk is the probability that an investment's actual return will be different than expected. Risk is calculated by taking returns of securities in last 3 years (12quarters).

Beta: Beta coefficient, a parameter in Capital Asset Pricing Model that describes how sensitive the expected return of a stock (or portfolio) is to the market. Data has been collected of last 3 years (12quarters).

This work describes two approaches for efficient measurement of units. These two approaches In brief are defined below-:

Approach 1: Data Envelope Analysis

Brief Explanation of the methodology can be defined taking an example of 2nd quarter in 2006

1) Earning per Share & Price to Earnings Ratio has been calculated from 1st quarter in 2006.
2) Standard Deviation & Beta has been calculated from 2nd quarter in 2003 to 1st quarter in 2006.
3) Using the Data, find the efficient securities using Efficient Measurement System (EMS).
4) Constructed portfolio by giving equal weights to each security.
5) Compared portfolio's return to market's return.

Approach 2: Shapre's Method:

Step 1: Calculate excess-return to β Ratio (Systematic Risk)

$$(R_i - R_f)/\beta_i$$

Step 2: Rank them in descending order.

Step 3: Calculate C for each security.

$$C = \sigma_N^2 \frac{\sum_{i=1}^{N} \frac{(R_i - R_f)\beta_i}{\sigma_{z_i}^2}}{1 + \sigma_N^2 \sum_{i=1}^{N} (\frac{\beta_i}{\sigma_{z_i}})^2}$$

Step 4: C will be increasing & then decreasing order so C* will be highest value among Cs.

Step 5: Find the optimum portfolio which is consisting of all securities which have $(R_i - R_f)/\beta$ > C*

Step 6: Calculate Z_i for each security included in portfolio.

$$Z_i = \frac{\beta_i}{\sigma^2_{Zi}}\left[\left(\frac{r_i - r_f}{\beta_i}\right) - C^*\right]$$

Step 7: Calculate weight X_i for each security Z_i

$$X_i = \frac{Z_i}{\sum Z}$$

Step 8: Multiply weights of each security to corresponding return of that forecasted quarter.
Step 9: Find return of optimal portfolio by adding all the retruns of each security.
Step 10: Compare return of optimal portfolio to market return.

RESULTS

DEA'S RESULTS

The application of DEA to stock selection resulted in a different number of stocks for each quarter along the 12 quarters analyzed. The average number of stocks in each quarter was seven. Also, it must be remembered that the procedure adopted was that each DEA-efficient stock would make up an equal fraction of the portfolio in one quarter and that it could be a candidate equally qualified to make up the portfolio in the following quarter. Table 1 to table 3 presents the 4 quarterly returns of each year for each of the market return and the result of portfolio made by DEA. One can observe that the return comes from the DEA made portfolio is better than the market return.

Table 1: Quarter-wise comparison of DEA's return & Market return in year 2005

Q1-05	RETURN	Q2-05	RETURN	Q3-05	RETURN	Q4-05	RETURN
HINDALCO	-0.07177	GRASIM	0.247462	GRASIM	0.053179	BHARTI	0.194244
ITC	0.22746	L&T	0.333965	L&T	0.219185	GRASIM	0.479209
INFOSYS	0.046658	AMBUJA	0.300847	ITC	0.038391	HINDALCO	0.272315
BHEL	0.127183	BAJAJ	0.291964	INFOSYS	0.190604	L&T	0.319054
BAJAJ	0.681177	RIL	0.236174	RE	0.037768	ITC	0.372887
HDFC	0.216557	SBI	0.377155	BHEL	0.132465	INFOSYS	-0.00531
DEA RETURN	0.204544		0.297928		0.111932		0.272067
MARKET RETURN	0.10797		0.200259		0.088419		0.20026

Table 2: Quarter-wise comparison of DEA's return & Market return in year 2006

Q1-06	RETURN	Q2-06	RETURN	Q3-06	RETURN	Q4-06	RETURN
GRASIM	-0.05069	ACC	0.267126	GRASIM	0.106939	HINDALCO	-0.0518
ICICI	-0.07285	ITC	0.12963	L&T	0.133459	L&T	0.122111
L&T	-0.0779	M&M	0.0955	HDFC	0.058822	HDFC	-0.0614
ITC	-0.05614	GRASIM	0.303323	RE	0.074863	M&M	-0.13876
INFOSYS	0.03244	RIL	0.160685	SBI	0.211611	INFOSYS	-0.10172
BHEL	-0.03133	CIPLA	0.215246	TCS	0.1928		
				HINDALCO	0.01605		
DEA RETURN	-0.04275		0.195252		0.113506		-0.04631
MARKET RETURN	-0.05946		0.1739		0.106		-0.05185

Table 3: Quarter-wise comparison of DEA's return & Market return in year 2007

Q1-07	RETURN	Q2-07	RETURN	Q3-07	RETURN	Q4-07	RETURN
BHARATI	0.09532	L&T	0.2807	L&T	0.4832	BHARATI	-0.069
L&T	0.35629	ITC	0.2262	RIL	0.2547	L&T	-0.174
RIL	0.24259	RIL	0.3504	GRASIM	0.1392	RIL	-0.21
TCS	-0.06656	HDFC	0.25780	HDFC	0.1365	BHEL	-0.204

RE	0.24023	INFOSYS	-.01682	INFOSYS	-0.067	ACC	-.19366
		TCS	0.24	BHEL	0.2713	AMBUJA	-0.175
				TCS	0.124	HDFC	-0.1703
						SBI	-.22566
DEA RETURN	0.17357		0.22304		0.1917		-0.1777
MARKET RETURN	0.1207		0.18023		0.1732		-0.2288

SHARPE'S METHOD:

The application of Sharpe's to stock selection resulted in a different number of stocks for each quarter along the 12 quarters analyzed. The average number of stocks in each quarter was three. Also, it must be remembered that the procedure adopted was that each Sharpe's efficient stock would make up a fraction calculated according to Sharpe's Method. Table 4 to table 6 presents the 4 quarterly returns of each year for each of the market return and the result of portfolio made by Sharpe's method One can observe the return comes from the Sharpe's made portfolio is not in accordance with the market return.

Table 4: Quarter-wise comparison of Sharpe's return & Market return in year 2005

Q1-05	RETURN	Q2-05	RETURN	Q3-05	RETURN	Q4-05	RETURN
GRASIM INDUSTRY	-5.7785	ITC LTD	0.925374	GRASIM INDUSTRY	-14.9394	L&T	11.8584
ITC LTD	0.29736	GRASIM INDUSTRY	0.045263	L&T	13.2349	BHEL	-3.55229
		L&T	0.029363			GRASIM INDUSTRY	0.958371
SHARPE'S RETURN	-5.00775		20.88137		-1.7045		9.264479
MARKET RETURN	0.10797		0.200259		0.088419		0.20026

Table 5: Quarter-wise comparison of Sharpe's return & Market return in year 2006

Q1-06	RETURN	Q2-06	RETURN	Q3-06	RETURN	Q4-06	RETURN
ICICI BANK	0.029734	L&T	-3.90796	BHEL	-34.9894	HDFC BANK	4.659699
L&T	3.174588	BHEL	-6.54485	RIL	2.002293	BHEL	-1.28275
BHEL	4.260967			L&T	-0.23452	GRASIM INDUSTRY	3.147726
GRASIM INDUSTRY	1.409107					L&T	1.085905
ACC	35.46602						
SHARPE'S RETURN	44.34041		-10.4528		-33.2217		7.610578
MARKET RETURN	-0.05946		0.1739		0.106		-0.05185

Table 6: Quarter-wise comparison of Sharpe's return & Market return in year 2007

Q1-07	RETURN	Q2-07	RETURN	Q3-07	RETURN	Q4-07	RETURN
ICICI BANK	-1.25743	RIL	11.53559	RIL	20.75588	RIL	20.75588
INFOSYS	-3.29691	L&T	10.7925	L&T	8.990838	L&T	8.156595
ITC LTD	-4.27426	HDFC	6.768974	GRASIM INDUSTRY	2.90491		
		GRASIM INDUSTRY	0.515803				
SHARPE'S RETURN	-8.8286		29.61286		32.65162		28.91247
MARKET RETURN	0.1207		0.18023		0.1732		-0.2288

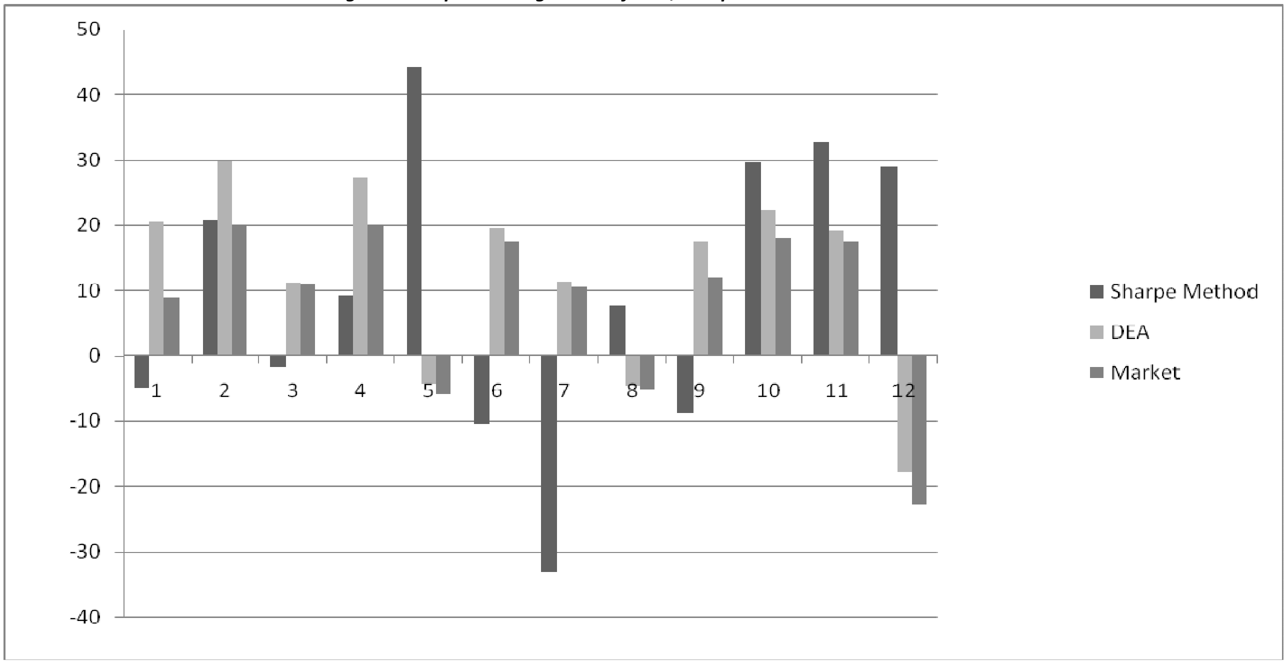
Table 7: ***Comparison of DEA, Sharpe's & Market's return***

	Sharpe Method	DEA	Market

Q1	-5.007747128	20.45435	8.841876
Q2	20.88136763	29.7928	20.02586
Q3	-1.704498631	11.19321	10.797
Q4	9.264479045	27.20673	20.02601
Q5	44.34041317	-4.27465	-5.94603
Q6	-10.45280802	19.52516	17.39
Q7	-33.22165555	11.35063	10.6
Q8	7.61057833	-4.63144	-5.1847
Q9	-8.828600991	17.35757	12.07
Q10	29.61286453	22.30468	18.023
Q11	32.65162457	19.17	17.32
Q12	28.91247114	-17.7703	-22.88
AM	09.5049	12.6399	08.4236
GM	07.2446	11.7162	07.5951

After comparing DEA return, Sharpe's Return and Market return graph was drawn

Figure 1: Graph showing return of DEA, Sharpe's & Market's return



FUTURE WORK

There is a lot of scope of future work related to portfolio optimization. These are:

- Out of three basic methods which one is better for portfolio optimization?
- Is variance a best measure of risk?
- Can high order moment replace variance as a measure of risk?
- How to develop model for many assets?
- How short selling can be allowed in that model?
- Which model is better to select assets?
- Which model is better to suggest for buy/sell?
- Data of inflation, GDP (Gross Domestic Product) how they affect market?

Introduction of a portfolio optimization model consisting n-assets, measuring risk more accurately and being able to apply it efficiently in long-short selling.

CONCLUSIONS

However Sharpe's method employs quadratic optimization to minimize the variance of the excess return of the manager over a linear combination of the asset classes.

- Comparing results of each quarter
  In each quarter DEA's return is more than Market's Return while in most of the cases Sharpe's return is less than Market's return.
- Comparing Arithmetic Means
  Arithmetic Mean shows that return by DEA is more.
- Comparing Geometric Means
  Geometric Mean signifies average of returns & if we compare them then DEA is better in this case also.

By this analysis we can say that DEA can gives better results in every aspect (long-term i.e. 3 years & short-term i.e. 3 months). So DEA is a better technique in finding efficient securities compared to Sharpe's Method.

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With sincere regards

Thanking you profoundly

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