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Portfolio revision by using data envelopment analysis model

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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. DEA model, originated from production industry, helps in selecting securities for portfolio. In this paper we have tried to find the right time to revise the portfolio by using DEA.

Keywords: portfolio revision, data envelopment analysis, stock market

Introduction

Portfolio-revision includes changing the current blend of securities. This might be affected either by changing the securities right now incorporated into the portfolio or by adjusting the extent of money invested into the securities. New securities might be added to the portfolio or a portion of the current securities might be expelled from the portfolio. Portfolio-revision in this manner prompts buys and offers of securities. The goal of Portfolio-revision is the same as the goal of portfolio choice, i.e. augmenting the arrival for a given level of hazard or limiting the hazard for a given level of return. A definitive aim of Portfolio-revision is amplification of return and minimization of risk.

The portfolio choice issue with one investment period is a specific instance of the general issue of picking between random factors when bigger results are favored. There is, along these lines, a requirement for models that settle on a decision between arbitrary factors (models for inclination). Fundamentally, there are three principle sorts of such models: mean-risk models, expected utility maximization, and stochastic dominance models. Mean-risks models are helpful from a computational perspective, however as a rule, contingent upon the hazard measure that is utilized, they may do not have a sane, hypothetical reason for settling on a decision. Therefore, the legitimacy of the outcomes gave is regularly faulty. Expected utility augmentation is typically hard to incorporate since the decision of an appropriate utility capacity is to some degree subjective. Stochastic model is especially imperative in venture issues since it depicts the inclination of reasonable and risk-averse investors.

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.

As of late, "data envelopment analysis" (DEA) has been utilized as a device to isolate the victor stocks from failure stocks. DEA is a linear programming based productivity assessment method created by Charnes *et al*. (1978) [3] and later altered by Banker *et al*. (1984). The DEA expect that "decision making units" (DMUs), for this situation firms, are effective if they utilize lesser inputs to make maximum output. The input parameters in this paper are identified with resource usage, liquidity and capital structure measures. The yield parameters are identified with development, valuation and benefit measures. In this unique circumstance, the DEA approach characterizes firms as proficient when they use resources successfully, are monetarily sound, encounter development, are generally reasonably valuated and are beneficial.

2. Literature Review

Markowitz (1952) [13] 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 (Pachamanova, 2006) [14]. 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 (Ceria & Stubbs, 2006) [4].

Full-scale streamlining depends on modern inquiry calculations to recognize the ideal portfolio given any arrangement of profit appropriations and based for any depiction of financial specialist inclinations. Full-scale advancement yields the genuinely ideal portfolio in test, while the mean—difference arrangement is a guess to the in-test truth. Both ways to deal with portfolio development, experience the ill effects of estimation blunder. Mean—change examination obliges financial specialists to gauge the methods and differences of all advantages and the co fluctuations of all benefit sets. To the degree the out-of-test understanding of these parameters leaves from the in-test parameter values, the mean-change estimation will be even less exact. Full-scale enhancement obliges speculators to gauge the whole multivariate return circulation. To the degree it fluctuates from the in-test appropriation, full-scale advancement will likewise yield problematic outcomes out of test.

Adler and Kritzman (2006) [1] utilized a bootstrapping strategy to think about the estimation mistake of full-scale streamlining to the joined guess and estimation blunder of mean-fluctuation investigation. They found that, to a critical degree, the in-test predominance of full-scale improvement wins out of test. They proposed that on the off chance that it is improved among resources those are probably going to have tireless non-typical higher minutes and it ought to be thought about edges or view additions and misfortunes in an unexpected way, it ought to be viewed as full-scale advancement as another option to mean-difference examination.

The idea of stochastic predominance or stochastic requesting of irregular factors was motivated by before work in the hypothesis of majorization that is, requesting. It has been utilized since the mid 1950's, in fields, for example, measurements. In financial aspects, stochastic strength was presented in the 1960's; Quirk and Saposnik considered the principal arrange stochastic predominance connection and exhibited the association with utility capacities. Second request stochastic predominance was conveyed to financial matters by Roman (2006) [17] exhibited a model for portfolio determination, which gives a significant arrangement, comparing to watched monetary conduct, and in the meantime is reasonable from a computational perspective. The arrangement is significant as in the chosen portfolio is non-overwhelmed as for second request stochastic strength (SSD) and along these lines ideal for each sound and hazard loath financial specialist. What's more, this portfolio has an arrival dissemination near a client determined target appropriation. Along these lines, this arrival appropriation can be molded and created to an attractive frame, to the degree that is achievable. On account of mean-hazard models steady with SSD, the main rule for choosing a particular portfolio is a coveted exchange off between mean return and hazard.

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 (1976) [18]. 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.

Enhancement of long-short portfolios using quick calculations exploits models of covariance to rearrange the conditions that decide optimality. Quick calculations exist for broadly connected variable and situation examination for long-just portfolios. To permit their utilization in component and situation investigation for long-short portfolios, the idea of "trim-capacity' is presented. The conclusion is that a similar quick calculations that were intended for long-no one but portfolios can be utilized, for all intents and purposes unaltered, for long-short portfolio improvement gave that portfolio is trim-capable, which more often than not holds practically speaking (Jacobs, *et al*, 2006) [11]. Practical models of long-short portfolio limitations can be composed as frameworks of straight balance or imbalance requirements.

The ideal modification of portfolio given the exchange expenses is considered as a mind boggling issue. It is examined in a few papers. Dybvig (2005) [7] utilizes a mean-change investigation of portfolio update given the exchange expenses to represent various imperative monetary components in a setting that is easy to comprehend and fathom totally. The outcomes uncover that the single-period case is suggestive of good techniques in more reasonable cases, and is a helpful benchmark for correlations. Lynch and Tan (2010) [12] add to the dynamic portfolio decision and the exchange cost literary works. They portray the financial specialist's ideal portfolio decision with corresponding and settled exchange costs, and with return consistency like that watched for the US securities exchange. The creators numerically observe the correction run to be a no-exchange area for the portfolio weights with amendment to the limit. Holden and Holden (2013) [10] talk about the ideal correction of portfolios with the exchange costs. They investigate both proportional and fixed transaction costs and show the existence of a no-trade region that is a fixed threshold for each investment with risk.

Ammann *et al*. (2006) [2] demonstrate that it is essential for financial specialists to realize what exchanging techniques an advantage supervisor seeks after to produce abundance returns. They propose an option approach for breaking down exchanging procedures utilized as a part of dynamic contributing. The creators apply the TEV as a measure of action to recognize the venture procedures of all benefit chiefs. Utilizing separation measure work (following mistake), De Waal and Bradfield (2003) [6] attempt to distinguish whether a current portfolio is sufficiently distinctive from an effective outskirts portfolio (representing resampling proficiency) to require rebuilding. The creators apply the factual comparability test to build up a zone that can be translated as a no-exchange zone. Tooth *et al*. (2006) propose a straight programming model for the portfolio update with the exchange costs in light of fluffy choice hypothesis. The calculation comes about demonstrate that the portfolio reconsidering model with a non-straight capacity can create a most loved portfolio correction procedure as indicated by the speculator's level of fulfillment.

Chen (2008) [5] utilizes information from Taiwan stock trade amid period 2004 to 2007 and the organizations comprise of concrete, nourishment, plastics, materials, hardware and apparatus, paper and mash, development and managing an account and protection businesses. Stocks and portfolios are picked and framed by the size and DEA models. The firm size was dictated by market value and the organizations were separated into little or huge in regards to the normal market value.

Patari *et al*. (2010) [15] utilize three diverse DEA models to frame portfolios. The DEA applications utilized are the variable comes back to scale, the super proficiency and the scale productivity demonstrate. The info variable is stock cost and yields are income per share, profit per share and book esteem per share. The portfolios are framed in view of the proficiency scores the stocks gotten in various DEA-approaches. Hazard balanced execution measurements and normal return is utilized to assess the execution of every portfolio. Likewise the effect of holding period length is considered in this review. Another review by Pätäri, Leivo and Honkapuro (2012) [16] concentrates the way toward utilizing DEA to frame value portfolios. The information is from the Helsinki stock Exchange and it comprises of the primary rundown firms from a time of 1994 to 2010. The DEA models utilized in their review are the consistent comes back to scale, the super-proficiency and cross-effectiveness models. Pätäri and al. (2012) [16] utilize four distinctive info and yield mixes with the DEA techniques noted in the past summarize.

Frijns, Margaritis and Psillaki (2012) [9] researched the use of DEA as venture system. They utilized a specimen of traded on an open market U.S. firms from period 1988-2007. As information sources they utilized net property, plant and gear, add up to long haul obligation, add up to resources, book estimation of value, capital use, expenses of products sold and offering, general and regulatory expenses.

3. Materials and methods

3.1 Research Objective

1. Portfolio selection by using Data Envelopment Analysis method.
2. Identify an efficient a portfolio revision period by using DEA

3.2 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 system construct just in light of the watched input yield information of firms or basic leadership units (DMUs). Because of this adaptable element it has been generally connected to people in general part ventures (Sengupta, 1999) [19]. Information envelopment examination is getting expanding significance as an apparatus for assessing and enhancing the execution of assembling and administration operations. It has been widely connected in execution assessment and benchmarking of schools, healing facilities, bank offices, generation plants, and so forth. (Talluri, 2000) [20]. DEA is usually used to assess the relative productivity of various makers. A run of the mill factual approach is described as a focal propensity approach and it assesses makers with respect to a normal maker. Interestingly, DEA is an extraordinary point technique and contrasts every maker and just the "best" makers. The fundamental deficiency in the normal measures of hazard balanced return is their failure to consolidate the expenses caused in creating the profits. In the late 1990s, a few reviews endeavoured to quantify oversaw portfolio execution by considering the arrival balanced for both hazard and cost, utilizing a non-parametric philosophy of creation outskirts estimation usually known as information envelopment examination (DEA) (Galagedera, 2000).

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.

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

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

$$u_r \text{ and } v_i \ge \epsilon \text{ with } r = 1,2,\dots\dots, s; i = 1,2,\dots\dots m \quad \text{Eq1}$$

where: k is the DMU under evaluation, yrj is the amount of output r of the DMUj; xij is the amount of input i of the DMUj; 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.

$$\text{Max } h_k = \sum_{r=1}^{s} u_r\, y_{rk}$$

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

$$\sum_{r=1}^{s} u_r y_{rj} \le \sum_{i=1}^{m} v_i x_{ij}, j = 1,2, \dots \dots, n$$
$$u_r, v_i \ge \epsilon \text{ with } r = 1,2, \dots., s; i = 1,2, \dots.. m \text{ Eq2}$$

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 [Talluri S].

For the purpose of this study we have taken BSE-30 index and considered following input and output financial parameters to identify efficient stocks for investment.

Table 1: The financial parameters used as inputs and outputs.

Input/output	Financial parameter
Input	Asset turnover
Input	Current ratio
Input	Quick ratio
Input	Debt to Equity
Output	Earnings yield
Output	Book to price
Output	Return on Assets
Output	Net profit margin
Output	Earnings per share

4. Results & Discussion

We have taken the 5 year data of input and output financial parameters from April-2011 to March-2016 and applied the Data envelopment analysis model for each year and the result is given in the following table.

Table 2: Year wise DEA portfolio and the portfolio return

2011-12	Return	2012-13	Return	2013-14	Return	2014-15	Return	2015-16	Return
Asian Paints	25%	Asian Paints	10%	Bajaj Auto	-15%	Coal India	5%	Asian Paints	12%
Bajaj Auto	18%	Bajaj Auto	17%	Coal India	25%	HDFC	14%	Bajaj Auto	19%
Coal India	-9%	Coal India	-6%	HDFC	30%	Hero Motors	11%	Coal India	14%
HDFC	21%	HDFC	7%	Hero Motors	18%	HUL	15%	HDFC	14%
Hero Motors	-25%	Hero Motors	28%	HUL	45%	Infosys	12%	HUL	15%
HUL	-10%	HUL	28%	Infosys	34%	ITC	15%	Infosys	16%
Infosys	10%	Infosys	11%	Maruti	30%	Maruti	30%	Maruti	20%
ITC	37%	ITC	15%	ONGC	-5%	ONGC	10%	Tata Steel	23%
Maruti	50%	Maruti	-4%	POWER GRID	25%	POWER GRID	10%	DRREDDY	13%
ONGC	16%	ONGC	3%	Tata Steel	-10%	Reliance	25%	L&T	19%
POWER GRID	10%	POWER GRID	12%			Tata Steel	10%		
Reliance	14%	Reliance	19%			Adani Power	14%		
Tata Steel	-14%	Tata Steel	25%			BHARTIARTL	10%		
TCS	32%	TCS	37%			DRREDDY	14%		
		NTPC limited	-16%						
Portfolio Return	12%	Portfolio Return	13%	Portfolio Return	18%	Portfolio return	14%	Portfolio Return	16%
Market return	-9%	Market return	12.6%	Portfolio Return	14.9%	Portfolio Return	20.5%	Portfolio Return	-5%
5 year Average market Return = 6.8%					5 year average return of DEA portfolio = 14.6%				
5 year Geometric market Return = 6.11%					5 year geometric return of DEA portfolio = 14.45%				

The above table 4.2 has mentioned the name of company which came as output of DEA model and their yearly return. The portfolio of each year has created by assigning equal weights to each DEA efficient company. The portfolio return of each year is 12%, 13%, 18%, 14%, 16 % and market return is -9%, 12.6%, 14.9%, 20.5%, -5% respectively for year from 2011 to 2016. The 5 year average and geometric return of DEA portfolio is 14.6%, 14.45% and for market it is 6.8%, 6.11% It is evident from the above data that portfolio created by DEA has outperformed the market.

If we invest at the starting of 2011-12 in the DEA selected companies for next five years then the total return is 52.5% and per year return is 10.5 % which is less than the per year average return if we revise the portfolio every year, the is mentioned in the following table 3.

Table 3: Return of DEA-Portfolio when invested for 5 year without revision

2011-12	Total 5 year Return
Asian Paints	65.0%
Bajaj Auto	58.0%
Coal India	31.0%
HDFC	61.0%
Hero Motors	15.0%
HUL	30.0%
Infosys	50.0%
ITC	77.0%
Maruti	90.0%
ONGC	56.0%
POWER GRID	50.0%
Reliance	54.0%
Tata Steel	26.0%
TCS	72.0%
Total 5 year return	**52.5%**
Per year avg return	**11%**
Total 5 year market return	**32.4%**
Per year avg market return	**6.48%**

5. Conclusions

This paper has compared the passive and active investment strategies and found that active investment strategies can give better return, if applied with some good model like Data envelopment analysis. In this paper we have used the DEA model to identify the efficient stock to invest every year from march-2011 to april-2016 and used two strategies for investment. In first strategies we have invested in DEA selected companies for one year and revise the portfolio each year through 5 year. In second strategy we have invested in DEA selected companies at the starting and stay invested for 5 years without revision. The result shows that the return of first strategy is better than the second one. So with the help of this paper we can conclude that investment with continuously revision of portfolio is better than stay invested in same portfolio.

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