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DATA ENVELOPMENT ANALYSIS OF LARGE-CAP SECURITIES OF THE ATHENS EXCHANGE

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Data Envelopment Analysis (DEA) is employed to measure for first time the relative efficiency of a sample of 59 large-cap stocks of the Athens Exchange, over the 2003-07 period and identifies these that have a collective set of attributes that dominate the others of the sample. A variable returns to scale (VRS) frontier, with the aid of benchmarks, classifies the stocks to efficient and inefficient ones according to a set of input attributes such as price to earnings (P/E) ratio, 1-year, 3-year and 5-year standard deviation and beta coefficient and output attributes like earnings per share (EPS) and returns on 1-year, 3-year and 5-year periods. The results suggest that maximum relative efficiency is related to the majority of the stocks under study and, moreover, that all stocks of the sample attained the highest expected return at the given level of their systematic risk. Furthermore, all stocks are DEA ranked while suggestions are put forward for the improvement of the DEA inefficient stocks.

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1. INTRODUCTION

One of the most important decisions that individuals and institutional investors face refers to the selection of investments to form a portfolio. The decision to purchase securities can be a difficult one since there are many attributes to consider associated either with the benefits or the costs from owing the stocks. The classical approach to portfolio optimization is the Markowitz (1952, 1959) covariance model. This model identifies an efficient frontier of portfolios that represent the best trade-offs of returns and risks measured by the variance of returns. The portfolios on this frontier need to be considered in investment decisions as they offer the highest possible expected return for a given level of risk or the lowest possible level of risk for a given expected return. Although the Markowitz covariance model forms the most universally accepted portfolio selection criterion, other models have been proposed to deal with risk-return considerations in alternate ways (Pardalos *et al.*, 1994; Elton and Gruber, 1995; Doumpos and Zopounidis, 2002; Spronk *et al.*, 2005). In recent years, criticism on these models has been increasing because of their disregard for individual investor preferences and their weakness to capture the multidimensional nature of the problem. As a result a multicriteria model based on more than the two criteria, expected return and risk, allows for higher flexibility in modeling the objectives of investors (Ehrgott *et al.*, 2004). More recently, Data Envelopment Analysis (DEA) has been applied in stock selection in a pioneering work by Powers and McMullen (2000). DEA is a multicriteria evaluating method that can select the most favorable alternatives among large sets using a mathematical programming algorithm. DEA provides a composite score - referred to as efficiency - for each alternative and this helps to simplify the complexity of analysis by evaluating the multi-criteria (Kadoya *et al.*, 2008). This paper employs DEA that incorporates multiple criteria along the lines suggested by Powers and McMullen (2000) and classifies, with the aid of benchmarks, the stocks of a sample of the Athens Exchange listed large-cap companies according to these criteria. In the DEA context, benchmarks are efficient stocks as defined in the multidimensional space where each dimension represents a different criterion. This approach has the advantage of simultaneously affording both a classification scheme and performance evaluation. The rest of the paper is organized as follows: Section 2 provides a brief overview on the theoretical background of DEA and Multi Criteria Decision Making (MCDM) methods and a review of studies on stock selection by means of DEA. Section 3 discusses the DEA method and the model used. Section 4 presents the data and empirical results and section 5 draws the conclusions and policy implications.

2. LITERATURE REVIEW

Within the past few decades various studies have been conducted on the relation between DEA and multi-criteria decision analysis (MCDA), see Belton and Vickers (1993), Stewart (1996), Cook and Kress (1991) and Cook *et al.* (1996). Stewart (1996) argues that DEA arises from situations where the goal is to determine the productive efficiency of a system or a unit by comparing how well the unit converts inputs into outputs, while MCDA models have arisen from the need to analyze a set of alternatives according to conflicting criteria. A methodological connection between MCDA and DEA is that if all criteria in a MCDA problem can be classified as either benefit criteria (i.e. maximizing benefits or outputs) or cost criteria (i.e. minimizing costs or inputs), then DEA is equivalent to MCDA. Maximizing and minimizing criteria are parts of MCDM terminology while outputs and inputs are their equivalents in DEA terminology, as by identifying whether a criterion is minimizing or maximizing it is possible to consider it as input or output in the DEA model, respectively. The basic function of DEA is to classify the units under evaluation in efficient and inefficient ones; in MCDA these can be regarded as non-dominated and dominated alternatives, respectively. DEA applications in portfolio selection are those of Powers and McMullen (2000), Tiryaki (2001) and Lopez *et al.* (2008). Other relevant applications of DEA in finance deal with the fundamental analysis of stocks (Abad *et al.*, 2004; Edirisinghe and Zhang, 2007, 2008), the ex-post evaluation of investment funds - a useful survey on this topic is provided by Alexakis and Tsolas (2005) - and the investment analysis (Kadoya, 2008). In our approach outlined in the following section DEA is used as a discrete MCDM method. A variable returns to scale (VRS) input oriented DEA based model is used to select the best stocks. DEA does not require any *a priori* weights for inputs and outputs. The relative efficiency of a production unit that is often referred as Decision Making Unit (DMU) is determined by assigning weights to the inputs and outputs of DMU so that the ratio of the weighted sum of outputs to the weighted sum of inputs is maximized. The weights of inputs and outputs are allowed to vary freely, that is within the constraints in each run of the value based DEA model (see Thanassoulis, 2001). As DEA models are run for each DMU, separately, the set of weights is typically different for the DMUs of the sample.

3. METHODOLOGY OF DATA ENVELOPMENT ANALYSIS

The DEA methodology, firstly proposed by Charnes *et al.* (1978) to evaluate the relative efficiency of DMUs, is a non-parametric method based on Farrell's (1957) method of efficiency measurement. Also, it does not require assumptions regarding the shape of the production frontier using simultaneously multiple inputs and outputs.

From a portfolio selection viewpoint the interest lies on identifying the stocks that represent the best trade-off between benefits and costs associated with owing the stocks. DEA does have potential for supporting stock selection providing a consolidated metric, the DEA score, that reflects the stocks' relative efficiency and it is used for choosing efficient stocks to construct an investment portfolio (Powers and McMullen, 2000). A benefit of DEA is that no *a priori* weight determination is required; instead, it provides a set of efficient outcomes based upon a set of *posteriori* weights determined objectively via an optimization process. Moreover, this technique can provide a consolidated metric, a composite score for each alternative which has simplifying value. The consolidated metric is derived by the running of a DEA model that must be repeated for each stock in the sample. The model computes the weights of the inputs and outputs so that the stock under evaluation is ranked as best as possible. The weights can differ from stock to stock. Furthermore, one of the main advantages of this approach is that DEA compares stocks to each other in order to determine their relative efficiency rather than examining each stock individually. Stocks need to be compared to each other before an analyst decides which one offers the best investment opportunities.

We use DEA to rank stocks on the basis of their attributes. An input-oriented DEA analysis will be conducted to identify those stocks that are efficient, as defined above, at a particular point of time. Given a set of j ($j = 1, 2,...,n$) stocks that have x_i ($i = 1, 2,\dots,m$) input attributes for which the goal has been set to be minimized and y_r ($r = 1, 2,\dots,s$) output attributes for which the goal has been set to be maximized, the efficiency indicator for every stock stems from the solution of the following linear programming problem (input-oriented VRS value based DEA model; see Thanassoulis, 2001):

$$Max \quad h = \sum_{r=1}^{s} \mu_r y_{r0} + \omega \tag{1.1}$$

s.t

$$\sum_{t=1}^{m} v_i x_{i0} = 1 \tag{1.2}$$

$$\sum_{r=1}^{s} \mu_r y_{r0} - \sum_{t=1}^{m} v_i x_{i0} + \omega \leq 0 \quad j = 1, 2, \cdots, n \tag{1.3}$$

$\mu_r \geq \varepsilon$ $\quad r = 1, 2,..., s$

$v_i \geq \varepsilon$ $\quad i = 1, 2,... m$

ω free on sign

where

$\varepsilon > 0$, a convenient small positive number (non-Archimedean), see also Charnes *et al.* (1994)

μ_r = output weights estimated by the model

v_i = input weights estimated by the model.

The dual of this equivalent linear programming model is the following model that is known as the 'BCC envelopment model':

$$Min\ \theta - \varepsilon\left(\sum_{r=1}^{k} s_r^+ + \sum_{i=1}^{m} s_i^-\right) \tag{2.1}$$

s.t.

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta\ x_{ij_0} \tag{2.2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rj_0} \tag{2.3}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{2.4}$$

$$\lambda_j,\ s_r^+,\ s_i^- \geq 0,\ j = 1, 2, \cdots, n, i = 1, 2, ...m, r = 1, 2, ..., k$$

where

y_{rj} = output attribute of stock j, r = 1, 2,…, k where k is the number of output attributes

x_{ij} = input level of stock j, i = 1, 2,…,m where m is the number of input attributes

n = total number of stocks

λ_j = intensity factor showing the contribution of stock j in the derivation of efficiency of stock '0'

s_r^+ = slack variable accounting for extra gains in output attribute r

s_i^- = slack variable accounting for extra savings in input attribute i

$\varepsilon > 0$, a convenient small positive number (non-Archimedean).

For each DMU that proves to be DEA-inefficient a hypothetical decision making unit can be composed as an aggregate of the DEA-efficient units, referred to as the efficient reference set for the inefficient unit (Adler *et al.*, 2002). In order to apply the models (1.1-1.3) and (2.1-2.4), model (1.1-1.3) provides the set of *posteriori* weights determined objectively via the optimization process, all inputs and outputs should have positive values. The envelopment form of the input-oriented BCC model (model 2.1-2.4) is translation invariant with respect to outputs and to non-discretionary inputs (Pastor and Ruiz, 2007). A model is considered translation invariant if the optimal value of the objective function, i.e. DEA score, is invariant for translations of the original input and output values consequent to an addition of a constant to the original data.

In this analysis, output attributes (i.e. earnings per share (EPS), returns for 1, 3 and 5 years) and price to earnings (P/E) ratios have negative values for some of stocks of the sample. It should be noted that although negative EPS and, as a result, negative P/E ratios are mathematically possible, they are generally not accepted in finance and are considered to be invalid or just not applicable. In this paper, however, the original data of negative EPS and P/E ratios are used properly transformed to feed the DEA model. Using the above transformation to convert negative original values so that the above mentioned attributes are translated into positive values the P/E ratio should be treated as non-discretionary, that is exogenously fixed, input (Thanassoulis, 2001). Therefore, the inputs are partitioned into two subsets, the discretionary inputs (beta coefficient and 1-year, 3-year and 5-year standard deviation) and the non-discretionary inputs (P/E ratio). Objective function (2.1) is replaced with (2.1*a*), restriction (2.2) is replaced with (2.2*a*) while a fourth restriction (2.2b) is added:

$$Min\ \theta - \varepsilon\left(\sum_{r=1}^{k} s_r^+ + \sum_{i \in D} s_i^-\right) \tag{2.1a}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta\ x_{ij_0}, i \in D \tag{2.2a}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ij_0}, i \in ND \tag{2.2b}$$

where D and ND refer to the sets of discretionary and non-discretionary input attributes, respectively.

In this new envelopment DEA model (model 2.1*a*, 2.2*a*, 2.2*b*, 2.3, 2.4) by using P/E ratio as a non discretionary input, a stock is considered efficient if none of its discretionary input attributes (i.e. beta coefficient and 1-year, 3-year and 5-year standard deviation of returns) can be reduced while at the same time retaining its output attributes constant. Efficiency as used here is not to be confused with its use in market capital theory where mean and variance of returns are the only two criteria. In our approach efficiency, considered as the objective function value of a linear programming model, describes the stocks of the sample with a set of attributes that collectively dominate the others based on the simultaneous analysis of all stocks and their attributes as described above. The efficiency indicators take values between 0 and 1. A stock is deemed DEA-efficient if the DEA score equals to unity, i.e. the costs (inputs) associated with owning the stock are offset by its benefits (outputs); otherwise, it is classified as DEA-inefficient (McMullen and Strong, 1998; Powers and McMullen, 2000).

4. DATA AND EMPIRICAL RESULTS

In the context of this paper, output attributes are assumed to be benefits and input attributes are assumed to be costs associated, respectively, with owning a specific stock. This is in line with the DEA context in which the relationship between inputs and outputs is considered. A total of nine attributes are considered. Four of the attributes are considered as outputs: EPS and 1-year, 3-year, and 5-year returns, while the remaining five attributes are considered as inputs: P/E ratio, beta coefficient, and 1-year, 3-year, and 5-year standard deviation of returns. The 59 largest market capitalization stocks of the Athens Exchange are examined that have been selected from Reuters' database. The sample data gathered refer to the daily close stock prices, the number of outstanding shares and financial statement data (earnings) of related listed firms. Each stock possesses a beta coefficient, that is a measure of its volatility relative to the Athens Exchange General Index, over the 2005-07 period.

The return for a period is calculated as follows:

$$R = (F_{t+1}-F_t)/F_t \quad (3)$$

where F_t = close price of the t_{th} day and

F_{t+1}= close price of the $t + 1_{th}$ day.

EPS is the ratio of earnings (i.e. after taxes net profit/loss with no adjustment for dividends) to the number of outstanding shares held in 31.12.2007. P/E is the ratio of stock close price in 31.12.2007 divided by EPS. Standard deviation, the dispersion of daily returns represents the total risk of stocks; it is calculated for 2007 (1-year), 2005-07 (3-year) and 2003-07 (5-year) periods. Table 1 reports the descriptive statistics for the variables used. The estimated efficiency scores of stocks derived by the model (2.1*a*, 2.2*a*, 2.2*b*, 2.3, 2.4) are summarized in Table 2 while they are presented in detail in Appendices 1 and 2. There are 34 stocks in 2003-07 period out of the sample of 59 stocks that have a score of 1 (100%) – the most efficient stocks, with a combination of 1-year, 3-year, and 5-year return, EPS, 1-year, 3-year, and 5-year standard deviation, beta coefficient, and P/E ratio that dominate all other stocks. They are on the efficiency frontier where there is no need for input attribute reduction. The average efficiency score for all stocks is 91.35%, which indicates a 8.65% required proportional reduction of their discretionary input attribute levels. It is worth noting that one stock with efficiency score 99.89% (i.e. near efficient stock) has been classified as inefficient.

Table 1
Descriptive Statistics of Stocks in the 2003-07 Period

	Beta coefficient	*P/E*	*Standard deviation of returns*			*Return*			*EPS*
			1-year	*3-year*	*5-year*	*1-year*	*3-year*	*5-year*	
Min	0.23	-89.05	0.16	0.35	0.51	-0.58	-0.74	-0.70	-1.32
Max	2.09	90.83	4.93	7.19	11.60	1.08	7.74	25.31	3.46
Mean	1.15	15.35	1.45	3.01	3.62	0.14	1.71	3.13	0.76
Median	1.13	15.31	1.10	2.97	2.98	0.07	1.35	1.71	0.66
Standard deviation	0.37	23.99	1.15	1.97	2.55	0.37	1.79	4.36	0.86

Number of stocks: 59

Table 2
Summary of Stock Efficiency Scores

Min	51.82%
Max	100.00%
Mean	91.35%
Median	100.00%
Standard deviation	0.13
Number of efficient stocks	34
Number of efficient stocks (% number of stocks in the sample)	58%

Number of stocks: 59

In addition, the sources of inefficiency for the non-efficient stocks can be identified by examining the slacks of the input variables. Table 3 depicts the relative mean slacks (absolute mean slack of an input divided by mean value of the input) of the input variables (Murthi *et al.*, 1997). Using the relative slacks one can compare the marginal impact of input attribute on a stock's output attributes across the set of stocks, as these slacks measure where the input attributes of the stock are in excess. A striking result derived is that the systematic risk measured by the beta coefficient has virtually no slacks throughout all stocks. Moreover, the slacks for total risk measured by standard deviation are between 6.72% to 8.38%. In light of these results, it is evident that all the stocks of the sample seem to have attained the highest expected return at the given level of their systematic risk. With respect to the third input attribute, the P/E ratio, which is considered as a non-discretionary input in the analysis, it has larger slacks (9.95%) compared to the other inputs.

Table 3
Mean Slacks in Inputs* (P/E Ratio, Beta Coefficient, and 1-year, 3-year and 5-year Standard Deviation of Returns)

Beta coefficient	*P/E ratio*	*Standard deviation of returns*		
		1 year	*3 year*	*5 year*
0.00%	9.95%	7.18%	6.72%	8.38%

* Mean slack: absolute mean slack of an input for all stocks/mean value of the input for all stocks.

Among the group of 34 efficient stocks one could further differentiate based on the frequency of their appearance in the reference set of the inefficient stocks, an idea firstly developed by Charnes *et al.* (1985) (see also Adler *et al.*, 2002). Namely, one can use these frequencies to rank the 34 efficient stocks and then rank the rest of the stocks according to their DEA scores. Given the 34 efficient stocks out of the total sample of 59 stocks, at most, an efficient stock may appear 25 times in the reference set of inefficient stocks. The frequency of appearance of an efficient stock in an inefficient stock's reference set provides information on how many inefficient stocks are affected by the presence of the efficient stock and therefore one becomes able to further rank the efficient stocks. Corresponding selected results for the top 10 efficient stocks are included in Table 4, while the results for all 59 stocks are presented in the Appendices 1 and 2. These results reveal that there are differences regarding the impact of efficient stocks on inefficient stocks. For example, stock 11 appears 16 times in the reference set of inefficient stocks as opposed to stocks 29, 30, and 39 which appear 5 times as a reference stock.

Table 4
Frequency of Appearance of Top 10 Efficient Stocks in the Reference Set of Inefficient Stocks

Stocks	*Appearance in the reference set*	
	Number of times	*% Max number of times*
Stock 11	16	64.00%
Stock 54	15	60.00%
Stock 58	12	48.00%
Stock 32	10	40.00%
Stock 37	9	36.00%
Stock 25	8	32.00%
Stock 12	6	24.00%
Stock 29	5	20.00%
Stock 30	5	20.00%
Stock 39	5	20.00%

The results derived in this study can be useful to potential investors in constructing their investment portfolios as this screening of stocks can be complemented with portfolio optimization methods to decide for the appropriate investment weights for their formed portfolio.

5. CONCLUDING REMARKS AND POLICY IMPLICATIONS

This paper has employed DEA to select the most efficient stocks from a sample of 59 of the large-cap stocks listed in the Athens Exchange. Three main reasons motivated the analysis, namely, the absence of prior DEA research on this topic in Greece, other stock characteristics than return and risk for investors' investment decisions, and the importance of identifying sources of DEA-inefficiencies in the stock selection problem for potential investors. DEA models can provide information to potential investors on which of the sample stocks are consistently the best when several attributes are considered. Moreover, the results can be used to estimate the level of improvement that is needed for each DEA-inefficient stock to become DEA-efficient with respect to its attributes. Within the DEA context it is shown that out of the 59 stocks evaluated, 34 are found to be relatively efficient or dominant. The empirical results indicate that the DEA-efficient stocks form the majority of the stocks under review while all stocks of the sample have attained the highest expected return at the given level of their systematic risk as it is measured by the beta coefficient. Furthermore, the main source of inefficiency for the remaining 25 stocks refers to the higher values of P/E ratio of the inefficient stocks and then follows the standard deviation of returns. A further screening of the efficient stocks that was undertaken through DEA, based on the frequency of their appearance in the reference set of inefficient stocks, can be useful to potential investors in constructing their investment portfolio and deciding their optimal investment weights employing one of the known optimization methods. Finally, this analysis has used an unbounded DEA model. The use of a weight restricted DEA algorithm can also be employed in cases where the potential users of the model aim at setting specific priorities that should be reflected by the weights of the model.

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APPENDICES

Appendix 1
Stock Efficiency Scores and Appearance of Efficient Stocks in Reference Set of Inefficient Stocks

Panel A: Efficient stocks

Stock No	*Ticker*	*Score*	*Appearance in reference set of inefficient stocks (number of times)*
11	HEPr.AT	100.00%	16
54	TELr.AT	100.00%	15
58	VOVr.AT	100.00%	12
32	EMDr.AT	100.00%	10
37	FRLr.AT	100.00%	9
25	ANKr.AT	100.00%	8
12	HLB.AT	100.00%	6
29	CORr.AT	100.00%	5
30	DOLr.AT	100.00%	5
39	HERr.AT	100.00%	5
8	FOLr.AT	100.00%	4
17	MYTr.AT	100.00%	4
49	NCHr.AT	100.00%	4
9	HDFr.AT	100.00%	3
33	EPAr.AT	100.00%	3
47	MILr.AT	100.00%	3
1	ACBr.AT	100.00%	2
6	DEHr.AT	100.00%	2
21	TTNr.AT	100.00%	2
23	ALAr.AT	100.00%	2
28	BABr.AT	100.00%	2
3	BOCr.AT	100.00%	1
36	FRIr.AT	100.00%	1
2	AGBr.AT	100.00%	0
4	BOPr.AT	100.00%	0
18	NBGr.AT	100.00%	0
34	EXCr.AT	100.00%	0
43	IQTr.AT	100.00%	0
44	LMDr.AT	100.00%	0
45	MAIr.AT	100.00%	0
46	MICr.AT	100.00%	0
51	PALr.AT	100.00%	0
53	SRSr.AT	100.00%	0
57	VIVr.AT	100.00%	0

Appendix 2
Stock Efficiency Scores

	Panel B: Inefficient stocks	
Stock No	*Ticker*	*Score*
16	MRFr.AT	99.89%
15	MORr.AT	97.48%
24	AMCr.AT	92.23%
10	HELr.AT	91.98%
19	OPAr.AT	91.92%
50	OLYr.AT	90.28%
20	OTEr.AT	84.55%
56	VAL.AT	83.59%
42	IASr.AT	83.22%
41	HYGr.AT	82.90%
27	AVAr.AT	82.51%
59	XAKO.AT	81.95%
52	SID.AT	81.37%
38	GHBr.AT	80.97%
35	EYDr.AT	79.60%
14	INRr.AT	78.85%
7	EFGr.AT	76.49%
13	INLr.AT	72.28%
26	ARCr.AT	71.21%
5	CBGr.AT	70.21%
31	EGNr.AT	70.17%
48	MTKr.AT	67.56%
22	VIO.AT	65.36%
40	HRMr.AT	61.24%
55	TERr.AT	51.82%