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Relative Performance of Equity Markets: An Assessment in the Conventional and Downside Frameworks

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ABSTRACT

This paper considers multiple measures of risk and return and appraises the performance of equity markets in the cross-section using a non-parametric procedure known as data envelopment analysis (DEA). In the appraisal, measures of risk (return) are treated as input (output) variables of the DEA model and developed and emerging markets are considered separately. The variation in relative performance among emerging markets is generally higher than that of developed markets. However, the overall performance of equity markets is consistent across the conventional and downside frameworks and the impact of risk measures on equity market performance is similar for both market types. Generally, the association between DEA ranking of markets and the ranking obtained with Treynor index are strong. The exception is when developed markets are ranked in the DEA models specified under the conventional framework.

JEL classification: C4, C67, G12, G15

Keywords: Relative performance; Emerging markets; Developed markets; Data envelopment analysis; Downside framework; Conventional framework

I. INTRODUCTION

In this paper we incorporate several measures of risk and return and assess in the cross-section the performance of global equity markets. The procedure we adopt here is known as data envelopment analysis (DEA). DEA is a non-parametric frontier analysis technique that can accommodate multiple inputs and outputs. Since DEA models can accommodate multiple inputs and outputs, performance evaluation using the DEA technique has advantages over the usual methods that adopt a single-output to single-input ratio. Further, DEA does not require specification of an efficiency frontier. DEA derives the frontier from observed data and assesses the performance of equity markets in relation to the established frontier of best performance. In DEA, equity markets themselves are used as benchmarks and therefore it is not necessary to refer to a benchmark. Our aim is to investigate relative influence of different types of risk measures on equity market performance when assessed using the DEA technique.

In DEA the units to be evaluated are required to be homogeneous. Studies have revealed that some characteristics of emerging markets may be different from of those of the developed markets. For example, Lagoarde-Segot and Lucey (2007) highlight illiquidity, low degree of competition, lack of market transparency and institutional specificities as factors typical to emerging markets. Another problem that is associated with emerging markets is thin trading. In other words, the operational environment of emerging markets may be different to that of developed markets. This raises the question of homogeneity of developed and emerging equity markets. Therefore, to satisfy the requirement of homogeneity in the equity markets being evaluated we assess the performance of developed and emerging markets separately and combined as a robustness check.

Asset pricing models may be broadly classified under two frameworks: conventional and downside. For a risk-averse investor, measures of risk defined in the downside framework (such as downside beta) is arguably more appealing than their counterparts in the conventional framework (such as CAPM beta). However, the studies that have compared the empirical usefulness of systematic risk in asset pricing in the conventional and downside frameworks report mixed results.[1]

For example, Pedersen and Hwang (2007) investigate the relative performance of the CAPM beta and downside beta as explanatory variables of individual equities and find that although downside beta explains equity returns better than the CAPM beta, the proportion of equities benefiting from using downside beta is not large enough to improve asset pricing models significantly. Estrada (2002), in an investigation of emerging market returns in the cross-section, reveals that downside risk measures such as semi-deviation and downside beta explains the variation in the returns better than the corresponding risk measures in the conventional framework.

Studies have applied the DEA technique to appraise performance of banks (Berger and Humphrey, 1997; Sathye, 2001; Jemric and Vujcic, 2002), insurance companies (Worthington and Hurley, 2002), credit unions (Gregoriou, Messier and Sedzro, 2004), enterprises (Yang, 2006; Gonzalez-Bravo, 2007), mutual funds (Murthi, Choi and Desai, 1997; McMullen and Strong, 1998; Basso and Funari, 2001; Galagedera and Silvapulle, 2002), hedge funds (Gregoriou, Sedzro and Zhu, 2005; Eling, 2006), securities (Powers and McMullen, 2000) and manufacturing industries

(Mahadevan, 2002). All these studies use risk measures as input variables and return measures as output variables in the DEA model.

In this study we consider two output variables and four input variables. The output variables (mean return and proportion of positive returns to total number of returns) are measures of return characteristics and the input variables are measures of systematic risk, total risk and idiosyncratic risk. The measures of risk considered in the conventional framework are- the CAPM beta, total risk, idiosyncratic risk and co-skewness and in the downside framework are - downside beta, total downside risk, idiosyncratic downside risk and downside co-skewness. We assess equity market performance using risk measures in the conventional framework and in the downside framework as separate input variable sets. The research questions we address here are: (i) whether there is a difference in equity market performance in the conventional and downside frameworks and (ii) whether certain risk measures have greater impact on equity market performance than some others when equity market performance is evaluated using DEA.

We observe that the overall performance of equity markets is consistent across the conventional and downside frameworks. When the relative performance of the two types of markets is assessed separately, the number of markets that fall on or lie closer to the frontier of best performance appears to be higher in developed markets than in emerging markets. Therefore, as expected the average performance of emerging markets is lower than that of the developed markets. This is an indication that the variation in relative performance among emerging markets is higher than the variation in relative performance among the developed markets.

The impact of input variables that we have considered here on equity market performance is generally not sensitive to market type. When assessing equity market performance using DEA, we observe that (i) it is sufficient to include either total risk or idiosyncratic risk in the model, (ii) total risk has a greater influence on performance than co-skewness and (iii) the effect of downside co-skewness on relative performance is negligible when downside beta is considered in the assessment. A high degree of variation in performance (discriminatory power) among equity markets is observed in the DEA models that include a standard systematic risk measure (CAPM beta or downside beta) and in the models that includes a measure of higher-order systematic risk (co-skewness or downside co-skewness) together with the corresponding standard systematic risk measure. In emerging markets there is a positive association between DEA ranking and the rankings obtained under the standard measures: Sharpe, Sortino and Treynor indices. The strongest association is observed with the Treynor index. However, in the case of developed markets there is weak evidence to suggest that DEA models specified under the conventional framework may have a decisive effect on the ranking compared to the rankings obtained under the standard measures. The DEA ranking is obtained assuming variable returns-to-scale and the ranking obtained with standard measures may be considered as scale invariant. While this may be a plausible reason for potential variation in ranking in DEA models and standard measures.

The rest of the paper is organised as follows. In the next section we describe the DEA technique in brief. The data is described in Section III followed by the methodology in Section IV. In Section V we discuss the results and in Section VI we check robustness of the results. The paper concludes with some remarks in Section VII.

II. DEA TECHNIQUE

The DEA technique defines an efficiency measure of a market by its position relative to the frontier of best performance. The observed data establish the frontier. It is made up of piece wise linear segments. The frontier of best performance is established mathematically by the ratio of a weighted sum of outputs to a weighted sum of inputs. The established frontier characterises the relative performance of markets and identifies poor performance based on known levels of attainment. Thus, a market contributes to the formation of the frontier only when it is not found to be inefficient in using the inputs to generate the output when compared with other markets in the sample. DEA assigns a score of 100 per cent to such markets. The markets that do not contribute to formation of the frontier are assigned scores less than 100 per cent and the scores depend on the position of these markets relative to the established frontier. A score less than 100 per cent suggest that a linear combination of other markets from the sample could produce the same vector of outputs using a smaller vector of inputs. There are a number of equivalent formulations for DEA. The original formulation of the DEA model by Charnes, Cooper and Rhodes (1978) denoted CCR hereafter is given next.

Let $S = \{1,...,s\}$ denote the set of outputs considered in the analysis, $M = \{1,...m\}$ the set of inputs considered in the analysis, y_{rj} = known positive output level of market $j, r \in S$, x_{ij} = known positive input level of market j, $i \in M$ and n = total number of markets evaluated. The CCR model for determining the relative performance of a designated market $'\kappa'$ is given as:

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

Subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 , \quad j = 1,2,...,n, \tag{2}$$

$$u_r,\ v_i \ge 0 , \quad r = 1,2,...,s, \text{ and } i = 1,2,...,m. \tag{3}$$

The above formulation assumes constant returns-to-scale and the frontier is a piecewise linear surface. The variables in the model are the input and output weights u_r and v_i respectively. The objective function (1) is the ratio of the weighted sum of outputs to the weighted sum of inputs of market $'k'$. The optimal values of the variables u_r and v_i are determined as a solution to the problem of maximising the performance measure of market $'k'$, subject to the constraint that the performance measures of all markets be less than or equal to one. The model (1-3) has an infinite number of optimal solutions, since if $\{u_r^*, v_i^*\}$ is an optimal solution, then $\{\alpha u_r^*, \alpha v_i^*\}$ will also be an optimal solution. One way of avoiding this is to impose the constraint $\sum_{i=1}^{m} v_i x_{ij} = 1$. The model (1-3) together with $\sum_{i=1}^{m} v_i x_{ij} = 1$ can be transformed to a linear programme. For every linear programme there is an associated linear programme called the 'dual'. The optimal solution to one model reveals the optimal solution to the other. Hence, the dual problem which always has a fewer number of constraints is the preferred form to handle. The dual model may be given as:

$$\text{Min } \theta \tag{4}$$

subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk}, \qquad r = 1,2,\ldots,s, \tag{5}$$

$$\theta x_{ik} \geq \sum_{j=1}^{n} \lambda_j x_{ij}, \qquad i = 1,2,\ldots,m, \tag{6}$$

$$\lambda_j \geq 0, \qquad j = 1,2,\ldots,n. \tag{7}$$

The variables in the model (4-7) are unrestricted θ and λ_j which is non-negative for all j. The variable θ is the proportional reduction in all inputs of the market 'k' required to achieve best performance or reach the frontier. The constraints in the model ensure that the relative performance of market 'k' never exceeds 1. The sufficient condition for a score of 100 per cent for market 'k' is that the optimum value of θ is 1. Otherwise, it is labelled as inefficient compared to the other markets in the sample.[2] The orientation of the model given in (4-7) is an input reduction approach since it provides information on how much proportional reduction of inputs is necessary (while maintaining output levels) for a market that fall short of the frontier to become a best performer.[3]

The formulation (4-7) falls under the constant returns to scale (CRS) type. The DEA score obtained from the solution to model (4-7) therefore, captures technical performance as well as performance due to the scale of operation. The variable returns-to-scale (VRS) version of the model (4-7) was proposed by Banker, Charnes and Cooper (1984) hereafter called the BCC model. The BCC model is (4-7) together with the additional constraint,

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{8}$$

which captures the returns-to-scale characteristics. The BCC model measures technical performance only. Hence, the scores obtained in the BCC model may be considered as estimates of 'pure' technical performance. The score obtained for a designated market under CRS is a measure of overall technical performance. The difference in overall performance and pure technical performance is attributed to the performance due to the scale of operation. A measure of performance due to the scale of operation is simply the ratio of overall performance and pure technical performance.

Hereafter we refer to the markets that contribute to the formation of the frontier of best performance as DEA-efficient (or efficient) markets and those markets that fall short of the established frontier as DEA-inefficient (or inefficient) markets. For an introduction to the theory and application of DEA, see Thanassoulis (2003).

III. DATA

We use daily price index of 22 developed and 22 emerging markets obtained from the MSCI database. The sample period is from 01 January 1993 to 23 February 2007. The exception is with Czech Republic, Hungary, Russia and Morocco where the data is collected from 01 January 1995 to 23 February 2007. The world index returns obtained from the MSCI database is considered as a proxy for the global market portfolio returns. The US 30-day T-Bill rate obtained from the US Federal Reserve Bank website is considered as the risk-free rate. Some summary statistics of the returns in the sampled markets are given in Table 1. Jarque-Bera test reveals that normality in the distribution of returns is rejected for all markets.

Table 1

Summary statistics of emerging and developed market daily returns

	Mean	Median	Min	Max	SD	Kurtosis	Skew	Jarque-Bera
Panel A: Emerging Markets								
1 Argentina	0.032	0.02	-33.65	16.34	2.29	24.59	-1.17	72521.8
2 Chile	0.031	0.00	-6.23	8.70	1.15	6.67	0.02	2068.9
3 China	-0.017	0.00	-14.44	12.74	1.91	8.21	0.07	4172.8
4 Colombia	0.045	0.00	-12.97	16.49	1.50	14.91	0.09	21810.1
5 Czech Rep	0.054	0.07	-7.39	8.76	1.52	5.28	-0.16	698.3
6 Hungary	0.071	0.09	-19.01	13.00	1.93	11.71	-0.53	10175.5
7 India	0.037	0.02	-11.95	8.26	1.57	6.78	-0.29	2248.4
8 Indonesia	0.008	0.02	-43.08	23.77	2.83	34.11	-1.23	149729.1
9 Israel	0.021	0.03	-9.79	8.28	1.51	7.37	-0.26	2982.8
10 Korea	0.030	0.00	-21.67	26.88	2.40	15.91	0.31	25695.7
11 Malaysia	0.014	0.00	-36.97	25.85	1.94	67.06	-0.82	631278.1
12 Mexico	0.040	0.05	-21.76	17.84	1.92	17.10	-0.10	30571.0
13 Morocco	0.044	0.03	-4.82	6.25	0.85	7.50	0.13	2685.1
14 Pakistan	0.014	0.00	-15.73	14.21	1.92	9.78	-0.45	7201.7

Table 1 (continued)

	Mean	Median	Min	Max	SD	Kurtosis	Skew	Jarque-Bera
15 Peru	0.058	0.03	-9.34	10.65	1.61	8.07	-0.08	3960.0
16 Philippines	0.000	0.00	-10.94	21.97	1.70	17.73	0.90	33838.2
17 Poland	0.070	0.02	-11.59	12.53	2.23	7.13	-0.16	2643.3
18 Russia	0.079	0.09	-28.10	24.22	3.19	12.07	-0.37	10948.5
19 South Africa	0.042	0.05	-13.02	11.26	1.54	8.93	-0.44	5529.6
20 Taiwan	0.016	0.00	-11.13	7.40	1.73	5.74	0.03	1156.3
21 Thailand	-0.011	-0.02	-18.08	18.10	2.17	13.50	0.66	17225.6
22 Turkey	0.052	0.05	-27.42	22.01	3.28	8.99	-0.24	5554.2
Panel B: Developed Markets								
1 Australia	0.038	0.04	-7.06	7.37	1.08	5.55	-0.17	1019.6
2 Austria	0.039	0.04	-6.29	4.88	1.07	5.43	-0.40	1007.9
3 Belgium	0.038	0.05	-6.39	8.73	1.12	7.71	0.11	3422.1
4 Canada	0.043	0.08	-9.72	5.23	1.09	8.87	-0.64	5550.6
5 Denmark	0.054	0.06	-6.25	5.56	1.11	5.41	-0.28	940.8
6 Finland	0.076	0.08	-20.07	15.91	2.19	10.29	-0.47	8299.6
7 France	0.037	0.07	-6.34	5.96	1.22	5.28	-0.15	814.7
8 Germany	0.037	0.06	-7.78	6.89	1.36	5.74	-0.20	1177.7
9 Hong Kong	0.027	0.00	-13.77	16.01	1.59	12.51	0.05	13900.2
10 Ireland	0.044	0.05	-7.98	5.96	1.16	7.08	-0.41	2657.8
11 Italy	0.040	0.04	-7.11	6.66	1.34	5.12	-0.06	695.8
12 Japan	0.012	0.00	-7.16	12.27	1.39	6.50	0.20	1908.1
13 Netherlands	0.037	0.06	-8.47	6.57	1.21	7.08	-0.20	2585.1
14 New Zealand	0.050	0.07	-9.47	7.21	1.29	7.01	-0.46	2599.8
15 Norway	0.026	0.05	-15.76	11.03	1.30	13.16	-0.51	16030.8
16 Portugal	0.038	0.03	-6.48	5.07	1.06	5.75	-0.16	1177.6
17 Singapore	0.025	0.04	-10.76	11.85	1.33	11.16	0.12	10237.6
18 Spain	0.052	0.06	-6.39	7.01	1.28	5.49	-0.10	960.3
19 Sweden	0.057	0.06	-9.67	11.41	1.58	6.58	-0.10	1973.1
20 Switzerland	0.047	0.06	-7.10	6.76	1.07	6.36	-0.12	1746.3
21 UK	0.029	0.04	-5.27	5.26	1.01	5.37	-0.18	884.3
22 USA	0.033	0.02	-6.97	5.61	1.00	7.29	-0.12	2836.2
World market	0.031	0.06	-4.52	4.60	0.78	6.08	-0.16	1474.1

Notes: The data range from 01 January 1993 to 23 February 2007. The exception is with Czech Republic, Hungary, Russia and Morocco where the data is collected from 01 January 1995 to 23 February 2007. Jarque-Bera statistic reveals that distributions of daily returns in all markets are non-normal.

IV. METHODOLOGY

Our aim is to assess equity market performance from two behavioural perspectives: conventional and downside. The details of the input and output variables considered in the analysis is described next. The analysis considers different DEA models and their specification is described in section B.

A. Input- Output Variables

The input variables measure four types of risk: *total risk*, *systematic risk*, *idiosyncratic risk* and *higher-order systematic risk*.[4] In the conventional framework standard deviation of returns measures total risk, the CAPM beta measures systematic risk, the standard deviation of the residuals in the market model estimates idiosyncratic risk and co-skewness measures higher-order systematic risk.[5,6] Their counterparts in the downside framework are: *total downside risk* measured as semi-deviation of returns, *systematic downside risk* as measured in the downside beta proposed by Bawa and Lindenberg (1977), *idiosyncratic downside risk* measured as standard deviation of the residuals in the downside market model and *higher-order systematic downside risk* as measured in downside co-skewness.[7] The input variables in the conventional (downside) framework are labelled IV1-IV4 (IV5-IV8). The variables and their corresponding labels are given in Table 2.

Table 2
Input and output variables considered in the DEA models

Input variables	
Conventional framework	Downside framework
IV1 CAPM beta (*systematic risk*)	IV5 Downside beta (*systematic downside risk*)
IV2 Standard deviation of returns (*total risk*)	IV6 Semi-deviation of returns (*total downside risk*)
IV3 Standard deviation of the market model residuals (*idiosyncratic risk*)	IV7 Standard deviation of the downside market model residuals (*idiosyncratic downside risk*)
IV4 Co-skewness (*higher-order systematic risk*)	IV8 Downside co-skewness (*higher-order systematic downside risk*)
Output variables	
OV1 Mean return (*average return)*	
OV2 Proportion of positive returns to total number of returns observed (*proportion positive*)	

We estimate the systematic downside risk in a model analogous to the traditional market model. We define downside market model as

$$R_{it} - R_{ft} = \beta_i^D \min(R_{mt} - R_{ft}, 0) + \varepsilon_{it}$$

where R_f is the risk-free rate, R_{it} is the return in equity market i and R_{mt} is the return in world market portfolio m in time period t. The Bawa and Lindenberg (1977) lower partial moment beta (downside beta) is given by

$$E[(R_{it} - R_f)\min(R_{mt} - R_f, 0)] / E[\min(R_{mt} - R_f, 0)]^2$$

and the downside co-skewness is defined as

$$E[(R_{it} - R_f)\min(R_{mt} - R_f, 0)^2] / E[\min(R_{mt} - R_f, 0)]^3 .$$

Semi-deviation is defined as $\sqrt{\sum(\min(R_{it} - \mu_i, 0)^2)/N}$ where μ_i is the mean return of equity market i and N is the number of observations.

The two output variables are: average continuously compounded daily return (*average return*) and proportion of days out of 3690 observation days where equity market return is positive (*proportion positive*). The average return and proportion positive are labelled as OV1 and OV2 respectively. In the DEA performance-measure, high output values are preferred to low output values and low input values are preferred to high input values. We include ‘proportion positive’ as an output variable on the notion that generally, investors may prefer positive returns to negative returns and therefore a high ‘proportion positive’ value may be preferred to a low ‘proportion positive’ value.

It is a requirement in DEA that input and output variables take positive values. The average return for China and Thailand are negative and therefore a constant was added to the average returns (output variable) of all equity markets to make the mean return positive. Because of the translation invariance property in the chosen type of DEA model (BCC and input orientation) adding a constant to all values of an output variable does not affect DEA scores.[8] Further, we observe that certain pairs of input variables under a given framework are highly correlated. For example, the correlation between total risk (IV2) and idiosyncratic risk (IV3) is 0.90 (0.98) and between total downside risk (IV6) and idiosyncratic downside risk (IV7) is 0.96 (0.98) for developed (emerging) markets. DEA being a non-parametric technique does not suffer from multicollinearilty and therefore inclusion of correlated variables in the model is not a concern. Further, there is no evidence to suggest a strong association between highly correlated variables and changes in DEA-efficiency (Norman and Stoker, 1991).

B. DEA Model Specifications

The DEA score which measures relative performance depends on the choice of the input-output variable set. A simple application of a DEA model that includes all input and output variables deemed relevant for the analysis could result in (i) overestimation of efficiency of some markets and (ii) underestimation of efficiency of some markets that do not show extreme behaviour. In a given DEA model it is possible that a market may not show up as efficient even when it is performing well on average. To overcome such issues, studies of performance appraisal usually consider several DEA models. An analysis of several DEA models may reveal the overall behaviour of a market and the special features that may affect its performance (Gonzalez-Bravo, 2007). Therefore we consider several combinations of the input-output variables. Each DEA model is associated with a unique set of input-output variables. The DEA models considered in the analysis are presented in Table 3. Table 3 present sixteen DEA models (labelled C1-C16) used in the assessment of equity market performance in the conventional framework and sixteen model specifications (labelled D1-D16) used in the analysis in the downside framework. The input variable set of a model under the conventional (downside) framework is made up of the CAPM beta (downside beta) together with some combination of the other three input variables considered under that framework.[9] All models are solved for emerging and developed markets separately so that any issue such as level of integration thought to be different in the two types of markets may not violate the homogeneity requirement of markets being analysed. As a robustness check we solve the models with developed and emerging markets combined as well.

Table 3

Choice of input-output variables considered in the DEA models

Model	Input variables								Output variables		Total no of variables
	Conventional framework				Downside framework						
	IV1	IV2	IV3	IV4	IV5	IV6	IV7	IV8	OV1	OV2	
C1 (D1)	√				√				√		2
C2 (D2)	√	√			√	√			√		3
C3 (D3)	√		√		√		√		√		3
C4 (D4)	√			√	√			√	√		3
C5 (D5)	√	√		√	√	√		√	√		4
C6 (D6)	√	√	√	√	√	√	√	√	√		5
C7 (D7)	√				√				√	√	3
C8 (D8)	√	√			√	√			√	√	4
C9 (D9)	√		√		√		√		√	√	4
C10 (D10)	√			√	√			√	√	√	4
C11 (D11)	√	√		√	√	√		√	√	√	5
C12 (D12)	√	√	√	√	√	√	√	√	√	√	6
C13 (D13)	√	√	√		√	√	√		√		4
C14 (D14)	√	√	√		√	√	√		√	√	5
C15 (D15)	√		√	√	√		√	√	√		4
C16 (D16)	√		√	√	√		√	√	√	√	5

Notes: Ci indicates DEA model i specified under the conventional framework and Di indicates model i specified under the downside framework. For example, in model C1 the input variable is IV1 and the output variable is OV1 and in model D1 the input variable is IV5 and the output variable is OV1. The input and output variables are defined in Table 2.

Studies of performance evaluation of risky assets using DEA generally consider models with input orientation. For example, Murthi, Choi and Desai (1997), McMullen and Strong (1998) and Galagedera and Silvapulle (2002) when assessing mutual funds and Powers and McMullen (2000) when assessing securities using DEA assume input orientation and variable returns-to-scale. As we analyse a situation where output variables measure return characteristics and input variables measure risk characteristics we use input orientation DEA models. Then the resulting DEA scores reflect relative performance based on risk-adjusted return in a multi dimensional framework. Recall that in the performance measure (expression (1)) we may incorporate several risk measures and several return measures. A market that achieves a DEA-score of 100 per cent suggests that no other market or any combination of other markets may exceed its performance. All markets with 100 per cent score establish the frontier of best performance. If the DEA score of a market is less than 100 per cent, the score suggests the proportional reduction in the risk required, while maintaining the attained levels of return, to achieve 100 per cent DEA-efficiency or reach the established frontier of best performance. Higher the score the lesser the reduction in risk required to reach the frontier.

When classifying the units being assessed either as efficient or inefficient in DEA, Galagedera and Silvapulle (2003) in a simulation study of different types of production processes reveal that VRS specification appears to be a safer option in models with omitted variables. Hence, to guard against any adverse impact due to variables not considered in the analysis we impose the variable returns-to-scale assumption. In section VI.C we check robustness of the results by imposing the CRS assumption.

V. RESULTS AND DISCUSSION

A. Performance under Individual Indicators

First, we report the results of the analysis with single-output/single-input ratios (individual indicators). The two output variables and eight input variables considered in the analysis produce sixteen individual indicators (OVi/IVj: i=1,2; j=1,2,…,8). The equity market rankings based on the individual indicators for developed and emerging markets are given in Tables 4 and 5 respectively. The market with the highest (preferred) ratio is ranked 1 and the next highest ratio is ranked 2 and so on. The last column in Tables 4 and 5 gives the overall ranking based on the average individual ranks associated with the sixteen indicators. The overall ranking obtained through averaging may be considered as a global relative performance measure.

Table 4
Developed market ranking based on single output to single input ratios

Market	Rank																
	[OV1/ IV1]	[OV1/ IV2	[OV1/ IV3]	[OV1/ IV4	[OV1/ IV5]	[OV1/ IV6]	[OV1/ IV7]	[OV1/ IV8]	[OV2/ IV1]	[OV2/ IV2	[OV2/ IV3]	[OV2/ IV4	[OV2/ IV5]	[OV2/ IV6]	[OV2/ IV7]	[OV2/ IV8]	Overall rank
Australia	2	8	13	18	2	6	11	3	2	7	13	18	2	6	11	3	5
Austria	3	6	12	17	3	7	9	2	3	4	11	17	3	5	9	2	2
Belgium	11	9	7	1	10	9	7	11	11	9	7	1	9	8	5	11	6
Canada	14	7	3	20	15	8	3	16	14	3	3	20	14	7	3	15	11
Denmark	6	4	8	16	5	5	5	6	6	8	10	16	6	9	10	7	7
Finland	22	22	22	13	22	22	22	22	22	22	22	15	22	22	22	22	22
France	18	12	5	14	18	13	8	18	18	12	5	13	18	12	7	18	14
Germany	21	17	10	7	21	18	14	21	21	17	8	7	21	18	13	20	19
Hong Kong	8	21	21	21	9	21	21	9	8	21	21	21	8	21	21	9	20
Ireland	7	10	14	8	7	10	12	5	7	10	14	8	7	10	12	5	9
Italy	15	15	16	15	14	15	16	14	15	18	15	14	15	17	16	14	18
Japan	12	20	20	6	12	20	20	8	10	19	20	6	11	19	20	8	17
Netherlands	17	11	6	5	17	11	10	17	17	11	6	5	17	11	8	17	13
New Zealand	1	16	19	3	1	16	18	1	1	15	19	3	1	15	17	1	10
Norway	9	14	15	22	8	14	15	10	9	14	16	22	10	14	15	10	15
Portugal	4	5	9	19	6	4	6	7	5	6	9	19	5	4	6	6	4
Singapore	5	18	18	2	4	17	19	4	4	16	18	2	4	16	18	4	12
Spain	16	13	11	12	16	12	13	15	16	13	12	12	16	13	14	16	16
Sweden	20	19	17	11	20	19	17	19	20	20	17	11	20	20	19	21	21
Switzerland	10	3	4	10	11	2	4	12	12	5	4	10	12	3	4	12	3
UK	13	2	2	4	13	3	2	13	13	1	2	4	13	2	2	13	1
USA	19	1	1	9	19	1	1	20	19	2	1	9	19	1	1	19	8

Note: The output/input variables OV1-OV2 and IV1-IV8 are described in Table 2. Overall rank is based on average of ranks associated with the 16 individual indicators.

Table 5
Emerging market ranking based on single output to single input ratios

Market	Rank																
	[OV1/ IV1]	[OV1/ IV2	[OV1/ IV3]	[OV1/ IV4	[OV1/ IV5]	[OV1/ IV6]	[OV1/ IV7]	[OV1/ IV8]	[OV2/ IV1]	[OV2/ IV2	[OV2/ IV3]	[OV2/ IV4	[OV2/ IV5]	[OV2/ IV6]	[OV2/ IV7]	[OV2/ IV8]	Overall rank
Argentina	20	17	16	22	21	17	16	20	20	17	17	22	20	18	17	20	21
Chile	12	2	2	11	11	2	2	14	13	2	2	11	13	2	2	13	5
China	13	16	17	5	15	16	17	12	10	13	13	4	12	13	13	10	13
Colombia	4	4	6	8	3	4	5	4	4	6	6	9	4	4	6	5	2
Czech Rep	10	3	3	6	10	3	3	11	12	3	5	7	10	3	5	12	4
Hungary	17	9	9	12	16	9	9	15	18	11	11	13	17	12	11	16	14
India	3	7	8	9	4	7	8	3	3	7	7	10	3	8	7	4	3
Indonesia	9	21	21	7	9	22	21	7	8	20	20	6	8	20	20	6	16
Israel	19	8	5	4	19	8	7	19	19	4	3	5	18	5	3	17	10
Korea	15	18	18	18	17	18	18	16	14	19	19	18	16	19	19	15	19
Malaysia	7	15	15	20	7	14	15	8	6	14	14	19	7	14	14	8	12
Mexico	22	11	10	21	22	12	10	22	22	12	9	21	22	11	9	22	18
Morocco	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Pakistan	2	14	14	3	2	15	14	2	2	15	15	3	2	15	15	2	7
Peru	8	5	7	14	8	5	6	9	9	8	8	14	9	7	8	11	8
Philippines	5	12	12	10	5	11	12	5	5	9	10	8	5	9	10	3	6
Poland	14	13	13	15	12	13	13	13	15	16	16	15	14	16	16	14	17
Russia	21	20	20	17	20	20	20	21	21	21	21	20	21	21	21	21	22
South Africa	18	6	4	19	18	6	4	18	17	5	4	17	19	6	4	19	11
Taiwan	6	10	11	13	6	10	11	6	7	10	12	12	6	10	12	7	9
Thailand	11	19	19	2	13	19	19	10	11	18	18	2	11	17	18	9	15
Turkey	16	17	22	16	14	21	22	17	16	22	22	16	15	22	22	18	20

Note: The output/input variables OV1-OV2 and IV1-IV8 are described in Table 2. Overall rank is based on average of ranks associated with the 16 individual indicators.

The rankings reveal that the performance of a given equity market varies under different risk adjusted performance scenarios reflected by the pairs of variables used to construct the individual indicators. For example, the first row of Table 4 reveals that Australia is ranked 2 under four indicators (OV1/IV1, OV1/IV5, OV2/IV1 and OV2/IV5) and ranked 18 under OV1/IV4 and OV2/IV4. Under the other ten individual indicators the rank for Australia varies between 3 and 13. There is evidence that some markets may be ranked consistently either at the bottom or at the top. For example, Finland is ranked 22 (last) under fourteen of the sixteen ratios. Table 5 reveals that Morocco is ranked 1 under all 16 individual indicators. Further, there is evidence that markets that indicate good overall performance may not necessarily register the top rank under any of the individual indicators. As shown in the last column in Table 4, Austria is ranked 2 overall and is not ranked 1 under any individual indicator. Among the emerging markets Colombia registers the second best average ranking after Morocco. However, Colombia is not ranked 1 or 2 under any individual indicator and is ranked 3 only under one individual indicator.

As evident in Table 4, the top rank of developed markets is spread across 4 markets. The developed markets that register the top rank are Belgium (2 times), New Zealand (6 times), UK (1 time) and USA (7 times). UK is ranked 2 or 3 seven times followed by Australia (6 times) and Austria (6 times). Canada gets ranked either 2 or 3 on five occasions followed by Switzerland (3 times), New Zealand (2 times) and Singapore (2 times). USA is ranked 2 or 3 once. In other words, eight developed markets are ranked either 2 or 3 at least once under the sixteen individual indicators. Table 5 entries reveals that the top rank does not appear to spread across the emerging markets- the top rank is always registered by Morocco. However, seven emerging markets register rank 2 or 3 at least once under the sixteen individual indicators: Chile (8 times), Colombia (1 time), Czech Republic (6 times), India (4 times), Israel (2 times), Pakistan (8 times), Philippines (1 time) and Thailand (2 times).

Of the sampled emerging markets the best global relative performance is recorded for Morocco and that for developed markets is recorded for UK. Among the emerging (developed) markets Russia (Finland) registers the lowest ranking. Generally, there is no positive association between the global relative performance and the number of times the market is ranked high (1, 2 or 3) under the individual indicators. This is an indication that equity markets assessed with different single input and single output variable sets may produce varying performance levels. In this study we investigate equity market performance with different multiple input and multiple output variable combinations and this is done by using the nonparametric technique- DEA.

B. Performance under DEA

Here we discuss the DEA scores of emerging and developed markets computed in the thirty-two models given in Table 3 under the assumption of VRS and input orientation. The DEA model (BCC input orientation) that we use in the analysis gives the freedom to choose weights to both input and output variables of a market to maximise its performance and therefore it is possible that some markets may attain high scores (over estimation) due to particular combinations of the input-output variables. Underestimation of performance is also possible and that may stem from overlooking general behaviour to extreme behaviour (Gonzales-Bravo, 2007). Therefore we do not concentrate on relative performance of individual equity markets. Our aim is to investigate the influence of certain input variables under the conventional and downside frameworks on DEA-efficiency of equity markets. We investigate this based on average performance (average DEA-efficiency score) rather than relying on the efficiency scores of individual equity markets. Hence choice of weights or role of extreme behaviour is not a concern here.

Table 6
Summary of DEA efficiency of developed and emerging markets

Model	Developed markets				Emerging markets			
	NBPM	AP	SD	BPMs	NBPM	AP	SD	BPMs
Panel A: Conventional framework								
C1	4	62.9	25.0	1,5,6,14	3	32.7	37.7	13,17,18
C2	9	90.4	10.2	1,2,5,6,14,16,20,21,22	4	60.4	23.9	6,13,17,18
C3	7	89.6	10.4	1,2,5,6,14,20,22	4	61.8	23.7	6,13,17,18
C4	6	75.0	21.4	1,3,5,6,14,17	4	48.2	32.4	6,13,17,18
C5	11	92.8	9.2	1,2,3,5,6,14,16,17,20,21,22	4	63.1	23.1	6,13,17,18
C6	11	93.1	9.0	1,2,3,5,6,14,16,17,20,21,22	4	64.4	22.8	6,13,17,18
C7	5	70.4	25.6	1,4,5,6,14	5	39.8	39.3	5,6,13,17,18
C8	11	91.5	10.3	1,2,4,5,6,14,16,19,20,21,22	5	64.4	25.5	5,6,13,17,18
C9	9	91.0	10.4	1,2,4,5,6,14,19,2022	5	65.7	25.6	5,6,13,17,18
C10	8	79.3	21.6	1,3,4,5,6,14,17,19	5	53.8	32.2	5,6,13,17,18
C11	13	93.6	9.2	1,2,3,4,5,6,14,16,17,19,20,21,22	5	67.2	24.3	5,6,13,17,18
C12	13	94.3	8.7	1,2,3,4,5,6,14,16,17,19,20,21,22	5	68.3	24.4	5,6,13,17,18
C13	9	90.7	10.1	1,2,5,6,14,16,20,21,22	4	61.8	23.7	6,13,17,18
C14	11	91.6	10.2	1,2,4,5,6,14,16,19,20,21,22	5	65.7	25.7	5,6,13,17,18
C15	10	92.7	9.2	1,2,3,5,6,14,17,20,21,22	4	64.4	22.8	6,13,17,18
C16	12	94.0	8.9	1,2,3,4,5,6,14,17,19,20,21,22	5	68.3	24.4	5,6,13,17,18
Panel B: Downside framework								
D1	4	64.3	24.2	1,5,6,14	3	29.5	38.6	13,17,18
D2	8	90.1	10.1	1,5,6,14,16,20,21,22	4	58.8	24.8	6,13,17,18
D3	7	90.2	10.3	1,2,5,6,14,20,22	4	61.2	23.8	6,13,17,18
D4	5	65.2	24.2	1,2,5,6,14	3	29.5	38.6	13,17,18
D5	9	90.4	10.0	1,2,5,6,14,16,20,21,22	4	58.8	24.8	6,13,17,18
D6	9	90.8	9.9	1,2,5,6,14,16,20,21,22	4	61.3	23.9	6,13,17,18
D7	5	71.0	25.0	1,4,5,6,14	5	36.4	40.4	5,6,13,17,18
D8	11	91.7	10.3	1,2,4,5,6,14,16,19,20,21,22	5	63.0	26.4	5,6,13,17,18
D9	9	91.4	10.4	1,2,4,5,6,14,19,20,22	5	65.2	25.8	5,6,13,17,18
D10	6	72.2	24.8	1,2,4,5,6,14	5	36.4	40.4	5,6,13,17,18
D11	11	91.9	10.2	1,2,4,5,6,14,16,19,20,21,22	5	63.0	26.4	5,6,13,17,18
D12	11	92.0	10.0	1,2,4,5,6,14,16,19,20,21,22	5	65.2	25.8	5,6,13,17,18
D13	9	90.5	10.2	1,2,5,6,14,16,20,21,22	4	61.3	23.9	6,13,17,18
D14	11	91.9	10.2	1,2,4,5,6,14,16,19,20,21,22	5	65.2	25.8	5,6,13,17,18
D15	8	90.5	10.1	1,2,5,6,14,20,21,22	4	61.2	23.8	6,13,17,18
D16	10	91.7	10.2	1,2,4,5,6,14,19,20,21,22	5	65.2	25.8	5,6,13,17,18

Notes: The markets and their corresponding labels are given in Table 1. NBPM is the number of best performing (DEA-efficient) markets, AP is the average performance (average of 22 DEA scores), SD is the standard deviation of 22 DEA scores and BPMs are the best performing markets.

Under a given framework we investigate sixteen DEA models. Table 6 gives the number of equity markets deemed DEA-efficient, the average and the standard deviation of DEA scores, and the labels of the markets deemed DEA-efficient under each DEA model under a given framework and by market type. The score of an efficient market is 100 and inefficient markets are assigned scores less than 100. Panel A (Panel B) of Table 6 gives the results of the analysis under the conventional (downside) framework.

1. Developed versus Emerging Markets

The results reported in Table 6 reveals that the average performance of developed markets ranges from 62.9 (C1) and 94.3 (C12) whereas the range for emerging markets is between 29.5 (D1 and D4) and 68.3 (C12 and C14). Further, in a given DEA model the number of developed markets labelled efficient is always higher than the number labelled efficient for emerging markets. This is an indication that the number of developed markets close to the frontier of their best performance may be more than the number of emerging markets that may lie close to their frontier of best performance.

The average performance of developed (emerging) markets in the 16 models under the conventional framework and in the 16 models under the downside framework is 87.1 and 85.4 (59.4 and 55.1) respectively.[10] These observations suggest that overall performance of emerging and developed markets is consistent across the conventional and downside frameworks.

Generally, for developed markets the number of markets deemed efficient and the average performance in the models under the conventional framework is higher than in the corresponding models in the downside framework. Overall there appears to be a strong positive association between the number of efficient developed markets and average performance (correlation coefficient is 0.89 and 0.88 under the conventional and downside frameworks respectively). The association between the number of efficient emerging markets and average performance is low (the association under the conventional and downside frameworks is 0.46 and 0.48 respectively). This low association is not surprising given that the best performing emerging market set is stable across the DEA models considered in the analysis.

2. Conventional Framework versus Downside Framework

Table 6 entries reveal that the average performance varies considerably with the choice of the input variable set. For example, for developed (emerging) markets the average performance under model C1 is 62.9 (32.7) where as under model C2, the average performance is 90.4 (60.4). A similar observation is made in the results under the downside framework. A striking observation here is the variation in the number of efficient developed markets and the lack of variation in the number of efficient emerging markets across different DEA models. For example, in model C7 five developed markets are deemed efficient where as in model C12 the number of efficient developed markets is thirteen. In the case of emerging markets the number efficient under C7 and C12 is the same at 5. This is uncovered in the analysis of the results under the downside framework as well. A reason for the small number of efficient markets in C12 may be that the emerging market Morocco, which appears to be an outlier (is ranked top under each of the 16 individual indicators) influence the DEA-efficiency scores of some other emerging markets. We investigate this issue in section VI.A.

The average performance of equity markets reported in Panel A of Table 6 is similar to those of Panel B. This is an indication that the relative performance of equity markets when assessed using DEA under the conventional framework may be not very different from the relative performance when measured under the downside framework. Supporting evidence of this was found when we investigate this at the individual market level. This brings us to the question whether there is any association between DEA-efficiency and the performance revealed under individual indicators.

C. DEA Relative Efficiency versus Individual Indicator Performance

Here we discuss the association between the results obtained with individual indicators and different DEA models. More specifically, we investigate the number of times a given market is deemed efficient under the sixteen DEA models and the number of times that market is ranked 1, 2 or 3 under the sixteen individual indicators.

With developed markets (i) we observe a weak positive association (correlation coefficient is 0.21) between the number of times a market is deemed efficient under the sixteen DEA models and the number of times the market is ranked 1, 2 or 3 under the sixteen individual indicators and (ii) no association (correlation coefficient is -0.01) between the number of times a market is deemed efficient under the sixteen DEA models and its global relative performance. However, with emerging markets we observe the opposite. That is (i) no association (correlation is -0.09) between the number of times a market is deemed efficient under the sixteen DEA models and the number of times the market is ranked 1, 2 or 3 under the sixteen individual indicators and (ii) a positive association (correlation coefficient is 0.47) between the number of times a market is deemed efficient under the sixteen DEA models and its global relative performance.

D. Effect of Input Variables on DEA Efficiency

1. Developed Markets

In all DEA models considered in the analysis either the CAPM beta or the downside beta is included as an input variable. Therefore the effect of input variables discussed here is subject to one of systematic risk and systematic downside risk being in the DEA model.

First, we discuss the effect of total risk on DEA efficiency sore. The effect of total risk is assessed by comparing, other things being equal, the efficiency scores in models that include total risk as an input variable and the efficiency scores of models that does not include total risk as an input variable. In particular, we compare the efficiency scores of C1 with C2, C4 with C5, C7 with C8 and C10 with C11. The results given in Panel A of Table 6 reveal that total risk does affect the efficiency scores of developed markets. When total risk is included as an input variable in the DEA model a substantial increase in the number of efficient markets is observed thereby causing an increase in average efficiency. For example, the variable set of C1 consists of CAPM beta and average return and in C2 the variable set of C1 is augmented by including total risk as an input variable. The results reveal that the average efficiency of developed markets increases from 62.9 in C1 to 90.4 in C2 and the number of efficient markets also increase substantially from 4 in C1 to 9 in C2. The increase in efficiency is observed irrespective of which other input variable/s are in the model. Therefore total risk may be considered as a factor that affects DEA-efficiency score of developed markets.

Idiosyncratic risk also affects the relative performance of developed markets. Comparison of efficiency scores of C1 with C3 suggests that idiosyncratic risk as an input variable has a tendency to increase the number of developed markets labelled efficient than otherwise thereby causing an increase in average efficiency. However inclusion of idiosyncratic risk when total risk is already in the model does not bring about a significant change in average efficiency or efficiency set. This can be seen when efficiency scores of C5 is compared with C6 and that of C11 is compared with C12. Therefore when analysing developed market efficiency under the conventional framework using DEA, it may be sufficient to include only one of total risk and idiosyncratic risk in the DEA model. High correlation between total risk and idiosyncratic risk (correlation coefficient is 0.99) explains this result.

Comparison of the results of C1 with C4 and C7 with C10 suggests that higher-order systematic risk (co-skewness) also affects the relative performance of developed markets. When co-skewness is included as an input variable the average efficiency and the number of efficient developed markets increase. This is observed in spite of CAPM beta being in the model. This result indicates that co-skewness may be treated as a factor that may affect DEA-efficiency scores of developed markets.

Thus far we observed that inclusion of either total risk or co-skewness together with CAPM beta has a significant impact on DEA-efficiency scores. Now we discuss the impact of including total risk, co-skewness and CAPM beta together in the DEA model. This can be observed by comparing the results of C4 with C5 (average efficiency increases considerably from 75.0 to 92.8 and the number of efficient markets increases considerably from 6 to 11) and that of C2 with C5 (average efficiency increases marginally from 90.4 to 92.8 and the number of efficient markets increases from 9 to 11). It appears that total risk has a greater impact on DEA scores than co-skewness.

The results of DEA models in the downside framework reported in Panel B of Table 6 reveal that the effect of total downside risk and idiosyncratic downside risk on efficiency is similar to the effects of total risk and idiosyncratic risk observed in the models under the conventional framework. The effect of downside co-skewness on the performance of developed markets is not great when downside beta is in the model. For example, the average efficiency in D1 is 64.3 with 4 markets deemed efficient and when downside co-skewness is included (D4) the average increases marginally to 65.2 and the number of efficient markets increases only by 1. In other words, the relative ranking of developed markets under D1 and D4 virtually remains the same. The corresponding models under the conventional framework (C1 and C4) display a greater variation in efficiency scores.

A few DEA models considered under the conventional framework reveal Belgium and Singapore as efficient markets whereas no DEA model under the downside framework labels any of these markets efficient. When the second output variable- ‘proportion positive’ is included in the models in the conventional and in the downside framework Canada shows up efficient in addition to those that have already been classified as efficient. Overall, 'proportion positive' is not a factor that seems relevant in assessing the relative performance of equity markets using DEA.

Even though the sixteen different DEA models specified by different combinations of input-output variables reveals a variation in the number of efficient markets (the markets that establish the frontier of best performance) across different model specifications Australia, Denmark, Finland and New Zealand always lie on the established frontier of best performance.

2. Emerging Markets

The results obtained for emerging markets are reported in columns 6-9 of Table 6. The markets deemed efficient shown in column 9 of Table 6 reveals that the set of efficient emerging markets is not sensitive to the chosen variable set and therefore to the DEA model used. This observation is very different from the patterns observed in developed markets. The efficient emerging market set comprise of 3-5 markets out of Czech Republic, Hungary, Morocco, Poland and Russia. The results in column 9 of Table 6 reveal that Hungary is labelled DEA-efficient only in the models that include the output variable- 'proportion positive'.

With emerging markets, when total risk (total downside risk) is included in the model the average performance tends to increase. However, contrary to what is observed with developed markets, in spite of the increase in average performance the efficient market set virtually remains the same. For example, the average performance in C1 is 32.7 with Morocco, Poland and Russia labelled as DEA-efficient and when total risk is included (C2) the average performance increases to 60.4 with just one additional market (Finland) labelled DEA-efficient. A similar observation is made with D1 and D2.

The correlation between idiosyncratic risk (idiosyncratic downside risk) and total risk (total downside risk) is very high. Hence inclusion of idiosyncratic risk (idiosyncratic downside risk) together with total risk (total downside risk) does not have much of an impact on DEA efficiency scores. When idiosyncratic risk (idiosyncratic downside risk) is considered as an input variable without total risk (total downside risk), a substantial increase in average performance is observed.

Further, when co-skewness is included as an input variable, the average performance tends to increase while inclusion of downside co-skewness virtually has no effect on overall performance. A similar observation is made with developed markets. Here, the markets that always lie on the frontier irrespective of the DEA model used are Morocco, Poland and Russia.

In both types of markets, a comparison of the variation in DEA efficiency scores (based on coefficient of variation) reveals that the highest variation in equity market relative performance is observed in the DEA models that include the CAPM beta (Model C1) or the downside beta (Model D1) as the only input variable and in the models that include a measure of higher-order systematic risk together with the corresponding standard systematic risk measure (Models C4 and D4).

E. Comparison of Ranking in DEA and in Standard Measures

In the previous section we identified DEA models C1, D1, C4 and D4 provide the highest variability in DEA scores. In this section, we compare the ranking of the markets in these four DEA models with the ranking obtained in the Sharpe, Sortino and Treynor indices. The rankings are compared using the Spearman rank correlation coefficient.

We observe that in emerging markets DEA ranking is highly positively correlated with the rankings under the Treynor index. As expected the correlation here is stronger when Morocco, which appears to be an outlier, is left out of the sample. In the case of developed markets the correlation between the DEA rankings and the rankings obtained with Sharpe, Sortino and Treynor indices is positive only in the DEA models specified under the downside framework (models D1 and D4). When performance of developed markets is assessed using DEA models in the conventional framework (models C1 and C4), we observe a negative association between DEA rankings and the rankings of the other standard measures considered. This is an indication that DEA models can have a decisive effect on ranking of developed markets compared to the ranking obtained under standard measures. The DEA ranking is obtained assuming variable returns-to-scale and the ranking obtained with standard measures may be considered as scale invariant. This may be a plausible reason for potential variation in ranking in DEA models and standard measures.

VI. ROBUSTNESS OF THE RESULTS

A. Influence of Extreme Cases (Outliers)

We noted in the analysis of emerging markets Morocco is always ranked top under individual indicators suggesting that Morocco may be an extreme observation. Here we investigate whether inclusion of Morocco in the emerging market data set is the reason for observing that certain input variables have different effects on the efficiency of developed and emerging markets. This issue is investigated by removing Morocco from the emerging market set.

Now we observe that the effect of input variables on relative efficiency observed in the case of developed markets also hold with emerging markets. Like in the case with developed markets a variation in the number of markets deemed efficient across different DEA models is also observed here. The results reveal that Colombia, Hungary, Pakistan, Peru, Poland and Russia lie on the frontier of best performance irrespective of the choice of the input-output variable set.

B. Developed and Emerging Markets Combined

Now we discuss the performance of equity markets when both types of markets together are in the sample. Since Morocco appears to influence the DEA results, we removed Morocco from the pooled data set.

In models C1 and D1 none of the developed markets are deemed efficient. It appears that when the model considers the CAPM beta or the downside beta as the only input variable, the frontier of best performance is made up of emerging markets only. In the combined analysis a lesser number of emerging markets lie on the frontier of best performance than in the analysis of emerging markets separately. However, with a few exceptions, the developed markets that were shown up as efficient when the developed markets were analysed separately are also deemed efficient in the analysis with the pooled set. Hence the variability in the number of efficient developed markets across the models observed in the analysis with developed markets only is observed in the present analysis as well. In contrast, the efficient emerging market set is stable across the DEA models. In most cases six to seven emerging markets are revealed efficient.

C. Constant Returns-to-Scale

Here we discuss the relative performance of equity markets when the CRS assumption is made. When analysing emerging markets we omit Morocco to eliminate any influence due to extreme behaviour. When CRS is assumed our key findings under the VRS assumption remain largely unchanged.

D. Sub-Periods

Here we investigate whether our findings are sensitive to choice of sample period. For this we split the full period into two sub-periods: 01 January 1993 to 31 January 2000 and 01 February 2000 to 23 February 2007. The same set of markets is considered in both sub-periods and therefore the results across the sub-periods are comparable. In sub-period 1, the results are consistent with those that are reported in Table 6. In particular, more developed markets are deemed DEA-efficient compared to that of emerging markets and the variability in the DEA-efficiency scores of developed markets are lower than the variability in the DEA scores of emerging markets. During sub-period 1 the world index returns portray bullish behaviour. In sub-period 2, the variation in DEA scores of developed markets is higher and the number of developed markets deemed DEA-efficient is lower than in sub-period 1. This may be attributed to the nature of the world index returns in sub-period 2 where the returns display a downward trend followed by an upward trend. In sub-period 2, DEA analysis reveals that emerging markets perform, on average, better than in sub-period 1.

VII. CONCLUDING REMARKS

Using a non-parametric procedure known as data envelopment analysis (DEA), this study assesses the performance of 22 emerging and 22 developed equity markets separately considering several measures of risk and return in the conventional and downside frameworks. The analysis is based on sixteen different DEA models specified by different combinations of four input variables (systematic risk, total risk, idiosyncratic risk and higher-order systematic risk) and two output variables (mean return and proportion of positive returns to total number of returns observed).

Generally, the set of markets deemed efficient (the markets that establish the frontier of best performance) under the conventional framework is higher than that in the downside framework. Further, as expected the developed markets are generally closer to the frontier of their best performance than the emerging markets relative to their frontier.

The input variables that have been considered here have similar effects on the performance in both types of markets. In particular, (i) when total risk is considered in addition to the systematic risk the overall performance is improved, (ii) it is sufficient to include only one of total risk and idiosyncratic risk in the assessment, (iii) the higher-order systematic risk measure tends to increase overall performance in models specified under the conventional framework and (iv) total risk has a greater influence on overall performance than the higher-order systematic risk measure. Even though the number of markets deemed efficient across different model specifications under the conventional and downside frameworks varies, the overall performance of equity markets under the two types of frameworks is similar.

In the DEA models that include the standard systematic risk measure (CAPM beta/downside beta) and in the models that includes a measure of higher-order systematic risk (co-skewness/downside co-skewness) together with the corresponding standard systematic risk measure, the variation in equity market relative performance is generally higher than when total risk or idiosyncratic risk is included.

Generally, the association between DEA ranking and the ranking obtained with Treynor index are strong. The exception is when developed markets are ranked in the DEA models specified under the conventional framework. In that case there is weak evidence to suggest that DEA models may have a decisive effect on the ranking compared to the rankings obtained under the standard measures such as Sharpe, Sortino and Treynor indices.

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ENDNOTES

1. Usually empirical investigations of risk-return relationship adopt equilibrium pricing models that have been derived under various assumptions on investor behaviour and market conditions. A widely used pricing model is the capital asset pricing model (CAPM). An assumption of the CAPM is that the variance measures risk. This is questionable since variance treats positive and negative returns equally. In the CAPM, the systematic risk of an asset referred to as the beta is measured through co-moment of asset and market portfolio returns. An alternative measure of systematic risk is downside beta. Downside risk evolves from the notion that risk may be an asymmetric phenomenon. In the measurement of risk in the downside framework returns above a threshold is ignored.
2. A DEA run will produce a relative performance score, θ and a set of λ_j, $j = 1,2,...,n$ values for each market. The set of λ_j values of each market defines a point on the frontier of best performance made up of a convex combination of the markets that lie on it. Therefore, for a market that does not lie on the frontier, the point so defined by the λ_j values becomes a role model that in turn establishes precedence for it to become a best performer. The set of best performing markets

$\{j : \lambda_j > 0\}$ is called the reference set of the designated market, *k*. The reference set defines a linear segment of the DEA frontier against which the designated unit k's performance is measured. This linear segment can be thought of as a local approximation to the unknown efficient frontier.

3. A DEA model can be analysed in two ways: an input orientation and an output orientation. An output orientation analysis provides information on how much augmentation to the outputs of a market that fails to reach the frontier is necessary (while maintaining input levels) for it to become a best performer. When both input and output oriented models are analysed, the markets that fall short of the frontier can be viewed as input excessive (high risk), output deficient (low return) or some combination of both (McMullen and Strong, 1998).
4. Higher-order moments capture asymmetry. This has prompted researchers to consider higher-order co-moments in asset pricing models. See for example, Kraus and Litzenberger (1976), Christie-David and Chaudhry (2001) and Hwang and Satchell (1999).
5. The CAPM beta is estimated in the slope coefficient of the market model given by $R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_{it}$. Co-skewness is computed using $E\left[(r_{it} - \bar{r}_i)(r_{mt} - \bar{r}_m)^2\right] / E(r_{mt} - \bar{r}_m)^3$ where *r* represents return in excess of the risk-free rate.
6. The price of co-skewness risk is expected to have the opposite sign to the skewness of the world market portfolio return distribution (Kraus and Litzenberger, 1976). In our data set world index return distribution is negatively skewed and therefore we may treat co-skewness (is positive for all sampled countries) as an input variable.
7. Bawa and Lindenberg (1977) introduced a measure of downside risk that we refer to as the downside beta, based on the concept of lower partial moment (LPM). The LPM measures risk focussing on returns below an arbitrarily chosen threshold. The most commonly used threshold is the risk-free rate. The downside beta proposed in Estrada (2002) cannot be linked to a well-behaved utility function due to the focus only on negative returns and therefore we opted to use the downside beta proposed by Bawa and Lindenberg (1977).
8. An efficiency estimator which is not affected by adding constants to the variables is labelled translation invariant (Gstach, 2002). The input-oriented BCC model is translation invariant with respect to outputs (Cooper, Seiford, and Tone, 2000).
9. Under the conventional (downside) framework the standard measure of systematic risk is CAPM beta (downside beta). Therefore, in all DEA models under a given framework we include the standard measure of systematic risk associated with that framework.
10. 87.1 is the average of the average performance in C1-C16 given in column 3 in Panel A of Table 6.

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