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Full Length Research Paper

Evaluation of human resources in science and technology by using dynamic Malmquist index approach and window analysis

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Human resources in science and technology (HRST) are important for promoting national competitiveness. The capacity utilization of HRST refers to the ratio of the amount of output that can be produced using the installed productivity capacity to the optimal output. This study uses data envelopment analysis (DEA) to measure the capacity utilization of global ten countries. Six HRST productivity indexes from the 323 indexes listed in the world competitiveness yearbook published by IMD in 2010 were selected as a reference. In the process, a multiple criteria procedure is used to assess the performance in these nations. Observing the average efficiency values, Japan is the highest with a mean of 1.000. On top of that, Japan has the lowest standard deviation of 0.000. We also can see that the total productivity change score (MPI, Malmquist productivity indexes presented in column 5) is higher than one for almost all periods, except for 2008 to 2009 showing that a large proportion of group of ten countries experienced gains in total productivity in the five periods considered. The research provides evidence which establishes whether benchmarking provides a real and lasting benefit to nations. A series of managerial implications are set forth and discussed.

Key words*:* Malmquist index, window analysis, capacity utilization, data envelopment analysis (DEA).

INTRODUCTION

Krueger and Lindahl (2001) asserted that increasing the stock of human capital with higher education can promote technology improvement and economic growth. Simultaneously, developing the technology industry and stimulate the national economy. Therefore, with the lot of more higher education talent and more people that engaged in the work of science and relevant fields, it can improve the national competition advantage to heal. Productivity is the relationship between output and input. Meanwhile, efficiency indicates how to produce the maximum output while using the least amount of resource input (Caves et al., 1982). Capacity utilization (CU) is a key concern in measuring the productivity and efficiency of human resources in science and technology (HRST). CU denotes the ratio of actual output level to capacity output level, where capacity output level is the maximum capacity.

In this paper we apply a new approach based on frontier production function to research the productivity growth of human resources in science and technology. The research framework is that of data envelopment analysis (DEA). Data envelopment analysis (DEA) is a nonparametric method in operations research and economics for the estimation of production frontiers (Jahanshahloo, et al., 2009; Emrouznejad and Shale, 2009). It is used to empirically measure productive

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efficiency of decision making units. There are also parametric approaches which are used for the estimation of production frontiers. Under such a competitive environment, port performance measurement is not only a powerful management tool for port operators, but also constitutes a most important input for informing regional and national port planning and operations. In order to overcome this potential problem associated with an analysis based on cross-sectional data, in this paper DEA window analysis is, for the first time, applied to the port industry to deduce efficiency trends. Then, this paper continues conduct Malmquist productivity index (MPI) to estimate technological changes (Lozanoet al., 2011). MPI is defined using non-parametric distance functions, which determine how far a firm is from its optimal production given the observed output and applied input. MPI can decomposed the productivity growth into two mutually exclusive components: technical efficiency change and technical change overtime, which measures the change in efficiency frontier shift, respectively (Froot and Klemperer, 1989). These are: (i) technical efficiency change (*E*); (ii) technological change (*P*); (iii) pure technical efficiency change (*PT*); (iv) scale efficiency change (*S*); and (v) total factor productivity (*M*) change (Wang et al., 2008; Azizi and Jahed, 2011).

The reminder of this paper is as follows; research methods, DEA, includes the window analysis and Malmquist productivity indexes; introduction of the research design, which includes the research framework, research procedure and variable measurement and sample selection; dicussion of the empirical results; some managerial implications and ways of improving efficiency.

RESEARCH METHODS

DEA is a mathematical linear programming, approach based on the technical efficiency concept, it can be used to measure and analyze TE of different entities: productive and non productive, public and private, profit and nonprofit seeking firms (Azizi and Ajirlu, 2010; Lozano et al., 2011). The main advantages of DEA that make it suitable for measuring the efficiency of vehicle inspection agencies are: (i) it allows the simultaneous analysis of multiple outputs and multiple inputs, (ii) it does not require an explicit a priori determination of a production function, (iii) efficiency is measured relative to the highest observed performance rather than against some average and (iv) it does not require information on prices (Odeck, 2000; Azizi and Ajirlu, 2010; Shokouhi et al., 2010). It is a non-parametric approach that calculates efficiency level by doing linear program for each unit in the sample. DEA measures the efficiency of the decision-making unit by the comparison with best producer in the sample to derive compared efficiency.

As we have seen DEA is based on TE concept which is formula (1) (Wang et al., 2011):

$$\text{Technical efficiency } (TE) = \frac{\sum weighted\ output}{\sum weighted\ input} \tag{1}$$

Mathematically we can express the aforementioned relation by the following formula (2) (Wang et al., 2011):

$$E_k = \frac{\sum_{j=1}^{M} U_j O_{jk}}{\sum_{i=1}^{N} V_i I_{ik}} \tag{2}$$

E_k : TE for the DMU_k (between 0 and 1).

k : Number of DMU_k in the sample ($k = 1, \cdots, K$).

N : Number of the inputs used ($i = 1, \cdots, N$).

M : Number of outputs ($j = 1, \cdots, M$).

O_{jk} : The observed level of output j from DMU_k

I_{ik} : The observed level of input i from DMU_k

V_i : The weight of input i

U_j : The weight of output j

To measure TE for DMU_k by using linear program the following problem must be solved which is formula 3 (Odeck, 2000; Emrouznejad and Shale, 2009; Wang et al., 2011):

$$\begin{aligned} &MaxTE \\ &\quad S.to \\ &\quad Ek \le 1 \quad k = 1, 2, \cdots K \end{aligned} \tag{3}$$

Where TE is either maximizing outputs from given inputs, or minimizing inputs for a given level of outputs. The aafore-mentioned problem cannot be solved as stated because of difficulties associated with nonlinear (fractional) mathematical programming. Charnes et al. (1978) have developed a mathematical transformation which converts the above nonlinear programming to linear one.

Modified linear programming by the following formula (4) (Odeck, 2000; Emrouznejad and Shale, 2009; Wang et al., 2011):

$$\begin{aligned} &Max \sum_{j=1}^{M} U_j O_{jk} \\ &s.t. \\ &\sum_{i=1}^{N} V_i I_{ik} = 1 \\ &\sum_{j=1}^{M} U_j O_{jk} \le \sum_{i=1}^{N} V_i I_{ik} \\ &U_j, V_i \ge \varepsilon > 0 \end{aligned} \tag{4}$$

Window analysis

Based on rule of thumb, the number of DMU_k should be greater than double of the sum of inputs and outputs. In order to overcome the constraint of limited DMU_k in this study, the window analysis method proposed by Charnes et al. (1978) is adopted. Windows analysis is a time dependent version of DEA. In order to capture the variations of efficiency over time, Charnes et al. (1978) proposed a technique called 'window analysis' in DEA. Window analysis assesses the performance of a DMU_k over time by treating it as a different entity in each time period. This method allows for tracking the performance of a unit or a process (Soltanifar and Lotfi, 2011).

The basic idea is to regard each DMU_k as if it were a different DMU_k in each of the reporting dates. Then each DMU_k is not necessarily compared with the whole data set, but instead only with alternative subsets of panel data. The windows analysis is based on the assumption that what was feasible in the past remains feasible forever, and that the treatment of time in windows analysis is more in the nature of an averaging over the periods of time covered by the window (Tulkens et al., 1995; Khodabakhshi, 2010). DEA is initially used to analyze cross-sectional data, where a given DMU_k is compared with all other DMU_k that produce during the same time period and where the role of time is ignored. However, this can be rather misleading since a dynamic context may give rise to seemingly excessive use of resources that are intended to produce beneficial results in future periods. As such, panel data prevail over cross-sectional data in that not only do they enable a DMU_k to be compared with other counterparts, but also because the movement of efficiency of a particular DMU_k can be tracked over a period of time. In so doing, panel data are more likely to reflect the real efficiency of a DMU_k (Odeck, 2000; Lin, 2010; Lozano et al., 2011).

We briefly introduce the meaning of window analysis. Assume there are N alternatives, $l=1,\cdots,N$, and each alternatives has data for period 1 to M , $m=1,\cdots,M$. The window length is fixed to be K, the data from period $1,2,\cdots,K$ will form the first row, and the data from period $2,3,\cdots,K,K+1$ will form the second row, and so on. One more periods on the right will need to be shifted to, and a total of $M-K+1$ window rows are existed. Each window is represented by $i=1,\cdots,M-K+1$, and the ith window consists of the data in periods $j=i,\cdots,i+k-1.$ There are K sets of data to be evaluated. Therefore, there are a total of $N\times K$ DMU_k in that window (Odeck, 2000).

In order to apply window analysis, DEA is used to evaluate the performance of all DMU_k in the same window, and the efficiency, $E_{i,j}^l$, of each DMU will be entered in the right window position. The procedure will be repeated $M-K+1$ times to obtain all the efficiency values in all windows. Window analysis used all the efficiency values of an alternative to generate some statistics values. There include average efficiency (M_l), variance among efficiencies of alternative l (V_l), column range ($CR_{l,m}$), and the total range for alternative $l(TR_l)$ (Charnes et al., 1978).

The average efficiency (M_l) of alternative l is obtained by the following formula (5) (Odeck, 2000; Lin, 2010):

$$M_l=\frac{\sum_{t=1}^{M-k+1}\sum_{j=1}^{i+k-1}E_{i,j^l}}{K\times(M-K+1)},\quad l=1,\cdots,N \tag{5}$$

The variance among efficiencies of alternative l, V_l, is calculated by the following formula (6) (Odeck, 2000; Lin, 2010):

$$V_l=\frac{\sum_i^{M-K+1}\sum_j^{i+k-1}(E_{i,j}^l-M_l)^2}{K\times(M-K+1)-1},\quad l=1,\cdots,N \tag{6}$$

The variance of efficiency reflects the fluctuation of efficiency values for each alternative. If an alternative has higher average efficiency and small variance, its ranking can be higher compared to other alternatives.

Column range, $CR_{l,m}$, can be used to compare the fluctuations of efficiencies among the alternatives. In each alternative, because the data of the first period $(m=1)$ and last period $(m=M)$ are being analyzed in only the first and the $M-K+1$ window only one efficiency value is obtained for each of the two windows, the efficiencies in the first and last periods will not be included in the calculation of CR values. For the other periods, the data of each alternative is used at least twice and at least two efficiency values are available for calculating CR values.

$CR_{l,m}$ is the difference between the largest and the smallest efficiencies for alternative l in period m by the following formula (7) (Froot and Klemperer, 1989; Shahooth and Battall, 2006).

$$\begin{aligned}&CR_{l,m}=Max(E_{i,m}^l)-Min(E_{i,m}^l)\\&i=\max(m-k+1,1),\cdots,\min(m,M-K+1)\\&m=1,\cdots,M\end{aligned} \tag{7}$$

$CR_{l,m}$ can be used to evaluate the stability of efficiency of an alternative in each period. Then, CR_l is the overall column range for alternative l, and it shows the greatest variation in efficiency of an alternative over different periods by the following formula (8) (Shahooth and Battall, 2006; Cullinane et al., 2004):

$$CR_l=Max_{m=2,\cdots,M-1}(CR_{l,m}) \tag{8}$$

Finally, in order to understand the stability of an alternative over different periods, we can use total range to evaluate it. Total range is the difference between the maximum and minimum efficiency values of alternatives in all windows.

The total range (TR) for alternative l is formula 9 (Cullinane et al., 2004; Chang et al., 2007; Wang et al., 2008):

$$\begin{aligned}&TR_l=Max(E_{i,j}^l)-Min(E_{i,j}^l)\\&i=1,\cdots,M-K+1\\&j=i,\cdots,i+K-1\end{aligned} \tag{9}$$

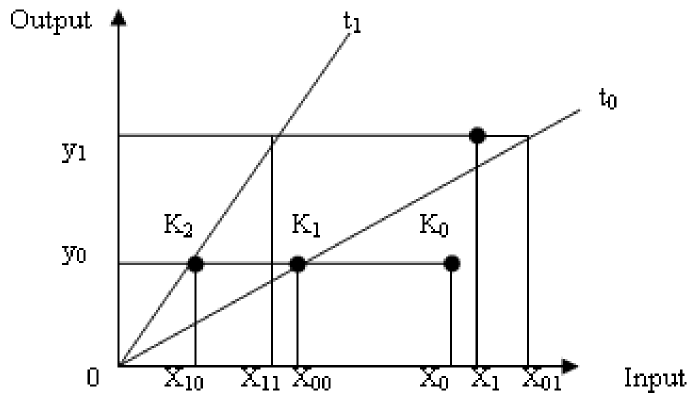

Figure 1. The MPI and its components. Source: Odeck (2000).

Window analysis of DEA has been adapted in many academic fields, such as industry analysis. Cullinane et al. (2004) apply DEA windows analysis to container port production efficiency. Shahooth and Battall (2006) use data envelopment analysis and window analysis in measuring and analyzing the relative cost efficiency of 24 Islamic banking institutions. Chang et al. (2007) applied window analysis to analyze dynamical efficiencies of Taiwan's TFT-LCD firms for the period of 2001 to 2005.

Malmquist productivity indexes (MPI)

The MPI were developed by Caves et al. (1982) based on the distance functions developed by Malmquist. Färe et al. decomposed the productivity growth into two mutually exclusive components: technical efficiency change and technical change overtime, which measures the change in efficiency frontier shift, respectively (Froot and Klemperer, 1989). The MPI expressed in DEA efficiency measures is defined as the ratio of the efficiency measures for the same production unit in two different time periods or between two different observations for the same period (Odeck, 2000; Rezitis, 2008).

The MPI for any unit between period 0 and 1 with frontier technology of period i as a reference, $M_i(0,1)$, can be calculated by using DEA measures obtained by solving the LP-problems (Odeck, 2000), which is formula 10.

$$M_i(0,1) = \frac{E_{i1}}{E_{i0}}, \quad i = 0,1 \in T \tag{10}$$

The i is the frontier technology, E_{i0} is the input (output) efficiency measure for a unit observed in period 0 and E_{i1} is input (output) efficiency for the same units observed in period 1 with technology i. The index, $M_i(0,1)$, shows the relative change in technical efficiency, and T represents the time period for the DMU_k.

Malmquist productivity indexes are based on nonparametric-parametric approach, which can capture the productivity change in economic growth using specific production function (Azizi and Jahed, 2011). The mathematics concept is borrowed from Odeck (2000) (Figure 1). The denominator shows the proportional adjustment of the observed input vector of the unit in period 1 for observed outputs to be on the same frontier function (Wang et al., 2011). The denominator is always between 0 and 1, while the numerator can be greater than 1. It follows that when $M_i(0,1)$ >1, then productivity has increased. If $M_i(0,1)$ < 1 then the productivity has decreased and if $M_i(0,1)$ =1 then productivity is unchanged. This holds irrespective of the reference technology (Odeck, 2000; Chen and Ali, 2004). Then, we can transform mathematics concept into a diagram, which is shown in Figure 1. The first year is t_0 and the second year is t_1. The model included one input variable (x) and one output variable (y). In the first year t_0, unit K_0 is observed with the combination (y_0, x_0), the corresponding benchmark units on the frontier are $K_1(y_0, x_{00})$ and $K_2(y_0, x_{10})$. The efficiency measures E_{00} and E_{10} are equal to the ratios (x_{00} / x_0) and (x_{10}, x_0). Therefore, the MPI can be written as follows Equation 11. Equation 11 indicates that the MPI is the change in productivity between the two periods (Odeck, 2000; Wei et al., 2007; Emrouznejad and Shale, 2009).

$$M_i(t_0, t_1) = \frac{E_{i1}}{E_{i0}} = \frac{x_{i1}/x_1}{x_{i0}/x_0} = \frac{y_1/x_1}{y_0/x_0} \tag{11}$$

In relation to Figure 1, the MPI can be decomposed into two parts, the first is the technical efficiency change (*E*) and the second is technological change (*P*), which is formula (12) (Odeck, 2000; Worthington, 1999; Pastor and Lovell, 2005).

$$M_i = E_i \times P_i, \quad i = 0,1$$

$$\begin{aligned} P_i(t_0, t_1) &= \frac{E_{01}}{E_{11}} = \frac{x_{01}/x_1}{x_{11}/x_1} = \frac{x_{12}}{x_{22}} \\ E_i(t_0, t_1) &= \frac{E_{11}}{E_{00}} = \frac{x_{11}/x_1}{x_{00}/x_0} = \frac{(y_1/x_1)(y_1/x_{11})}{(y_0/x_0)(y_0/x_{00})} = \frac{x_{11}}{x_{00}} \end{aligned} \tag{12}$$

Using these models, and the Fare et al. (1994) approach, it is thus possible to provide four efficiency/productivity indices for each firm and a measure of technical progress over time. These are: (i) technical efficiency change (*E*) (that is, relative to a constant returns-to-scale technology); (ii) technological change (*P*); (iii) pure technical efficiency change (*PT*) (that is, relative to a variable returns-to-scale technology); (iv) scale efficiency change (*S*); and (v) total factor productivity (*M*) change. Recalling that *M* indicates the degree of productivity change, then if $M > 1$ then productivity gains occur, whilst if $M < 1$ productivity losses occur. Regarding changes in efficiency, technical efficiency increases (decreases) if and only if *E* is greater (less) than one. An interpretation of the technological change index is that technical progress (regress) has occurred if *P* is greater (less) than one (Barros, 2008).

An assessment can also be made of the major sources of productivity gains/losses by comparing the values of *E* and *P*. If $E > P$ then productivity gains are largely the result of improvements in efficiency, whereas if $E < P$ productivity gains are primarily the result of technological progress. In addition, an indication of the major source of efficiency change can be obtained by recalling that overall technical efficiency is the product of pure technical efficiency and scale efficiency, such that $E = PT \times S$. Thus, if $PT > S$ then the major source of efficiency change (both increase and decrease) is improvement in pure technical efficiency, whereas if $PT < S$ the major source of efficiency is an improvement in scale efficiency.

There are many different research applied MPI to evaluate the cross-period efficiency. Worthington (1999) employed MPI productivity growth is decomposed into technical efficiency change and technological change for two hundred and sixty-nine Australian credit unions. Odeck (2000) used MPI to analyze efficiency and productivity growth of the Norwegian Motor Vehicle Inspection Agencies for the period 1989 to 1991. Zheng et al. (2003) investigated the productivity performance of SOEs using data envelopment analysis and a MPI based on a sample of about 600 state enterprises from 1980 to 1994. Chen and Ali (2004) proposed new approach not only reveals patterns of productivity change and presents a new interpretation along with the managerial implication of each Malmquist component, but also identifies the strategy shifts of individual DMU_k based upon isoquant changes. Pastor and Lovell (2005) propose a global MPI that give a single measure of productivity change. Zelenyuk (2006) find a theoretically justified method of aggregating MPI over individual decision making units into a group MPI . Wei et al. (2007) use MPI decomposition and investigate energy efficiency of China's iron and steel sector during the period 1994 to 2003. Liu and Wu (2007) used MPI to analyze the total factor productivity change in China's logistics industry with panel data of logistics listed corporation from 1999 to 2006. Liu and Wang (2008) employ data envelopment analysis to measure the MPI of semiconductor packaging and testing firms in Taiwan from 2000 to 2003. Barros (2008) estimates changes in total productivity, breaking this down into technically efficient change and technological change, by means of data envelopment analysis applied to the hydroelectric energy generating plants of EDP - the Portugal Electricity Company. Rezitis (2008) investigate the effect of acquisition activity on the efficiency and total factor productivity of Greek banks.

RESEARCH DESIGN

In this area, we propose our research framework and describe our variable measurement and sample selection.

Research framework

This research tries to measure the capacity utilization of HRST of group of ten for the period 2005 to 2010. The outputs to the model are three well known measures of overall performance: Skilled labor, overall productivity (PPP) and patents granted to residents determines the relative efficiencies of the first tier c in our sample in using the three inputs, Knowledge transfer, Funding for technological development and Total R and D personnel nationwide per capita, to generate the thee outputs. This allows identification of efficiency differentiators, which proves very useful for inefficient countries because it allows them to spot their weaknesses and improve performance. This study applies the DEA approach to reveal the extent to which inputs can be augmented while maintaining the same level of outputs. We employ window analysis to find out the long-term effectiveness in productivity. Finally, we adopt the MPI to identify the major source of productivity growth and separate the catching effect from efficiency changes over time due to technological advancements by using MPI . This study uses a DEA model to establish a foundation for measuring the efficiency of group of ten.

Variable measurement and sample selection

Frontier models require the identification of inputs (resources) and outputs (transformation of resources). Several criteria can be used in their selection. The first of these, an empirical criterion, is availability. Secondly, the literature survey is a way of ensuring the validity of the research and thus represents another criterion to be taken into account. The samples of this research are group of ten, which are Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom and USA. The period time of this research DMU_s is from 2005 to 2010. They are 60 totally. We use three input variables and three output variables. The input variables are knowledge transfer, funding for technological development and total R and D personnel nationwide per capital. The sources of data are from World Competitiveness Yearbook published by IMD in 2010.

EMPIRICAL RESULTS

This study uses the mathematical programming technique of DEA to estimate and assess CU of HRST. The DEA approach is a mathematical programming technique in which an optimal solution is determined according to a set of constraints. In this area, we conduct the window analysis and Malmquist productivity indexes analysis.

Window analysis

DEA window analysis can be done by excel solver via visual Basic application Microsoft Company, 2003 Microsoft Company, (2003), Excel Seattle, USA. In this paper, we assume constant returns to scale; that is, as all inputs double, all outputs will double. The window analysis enables us to identify the best and the worst countries in a relative sense, as well as the most stable and variable countries in DEA scores. The overall efficiency for each DMU_k is calculated by using CCR model, and the DEA window analysis is applied. The efficiency scores reported earlier are from panel data analyses, where the observations for group of ten in different years are treated as separate observations, and all measured against each other. This may not be a reasonable assumption because of technological improvements happening over the 7 year period under analysis, and that could make the comparison of units in different years unfair or unrealistic. The afore-mentioned results indicate this expected general tendency of improvements over time. To deal with the problem of unfair comparisons occurring when including all 7 years in the same analysis, we suggest using a window rather than a panel data approach, with a window width of 3 years. This means that observations are only compared to other observations within a 3-year time span.

The scores for a country in different years within the same window show how the efficiency of an industry changes from one year to another. The column view shows the efficiency for the same year but measured against different windows, and illustrates the impact of changing the units used to generate the frontier.

We can get the values of mean, standard division, column range and total range from the window analysis result. According to the value of mean, we can understand the long-term effectiveness in productivity. The variance of efficiency reflects the fluctuation of efficiency values for each alternative. column range, $CR_{l,m}$, can be used to compare the fluctuations of efficiencies among the alternatives. In order to understand the stability of an alternative over different periods, we can use total range to evaluate it. Total range is the difference between the maximum and minimum efficiency values of alternatives in all windows.

The information in Table 1 can be used to compare the performance of the different countries as illustrated in Figure 2. Figure 2 shows the average efficiency score for the different countries for each window in the analysis.

Observing the average efficiency values, Japan is the highest with a mean of 1.000. On top of that, Japan has the lowest standard division of 0.000. In a highly variant demand changing environment, Japan has a quite stabilized performance over the years.

The second best country is USA. It has relatively high efficiency over the periods, and their variances are not too big either; therefore, the overall performance of the system under USA is quite stabilized too. Regarding the CR value, the best country is Japan, and the second best is Italy. Japan also has the best TR value of 0.000, followed by Italy and USA.

Malmquist productivity indexes analysis

Malmquist indices for the period 2005 to 2010 are presented in Table 2 for the sample of group of ten. Using this information, two primary issues are addressed in our computation of Malmquist indices of productivity growth over the sample period. The first is the measurement of productivity change over the period. The second is to decompose changes in productivity into what are generally referred to as a ‘catching-up’ effect (efficiency change) and a ‘frontier shift’ effect (technological change). In turn, the ‘catching-up’ effect is further decomposed to identify the main source of improvement, through either enhancements in technical efficiency or increases in scale efficiency (Worthington, 1999).

DEA allows for the estimation of total productivity change in the form of the Malmquist index. The results are presented in Table 2, with the Malmquist index, denoted total productivity change, broken down into technically efficient change (the diffusion or catch-up component) and technologically efficient change. Moreover, we break down technically efficient change into pure efficient change and scale-efficient change. The group of ten is ranked according to the results of column 5.

In Table 2, we can see that the total productivity change score (the MPI presented in column 5) is higher than one for almost all periods, except for 2008 to 2009 showing that a large proportion of group of ten countries experienced gains in total productivity in the five periods considered. The mean MPI is 1.013, which, since it is higher than one, signifies that for the group of ten, total productivity increased from 2005 to 2010.

In Table 3, we can see that the total productivity change score (the MPI presented in column 5) is higher than one for France, Germany, Italy, Netherlands, Sweden, and Switzerland showing that a large proportion of the six countries experienced gains in total productivity in the period considered. The mean MPI is 1.013, which, since it is higher than one, signifies that for the group of ten, total productivity decreased from 2005 to 2010. The change in the technical efficiency score (column 1) is defined as the diffusion of best-practice technology in the management of the activity and is attributed to investment planning, technical experience and management and organization in the Group of Ten. For the period under analysis, we can see that it is higher than one for Canada, France, Germany, Italy, Netherlands, Sweden, Switzerland and USA, signifying that there was an increase in technical efficiency in the period. However, for Japan, and United Kingdom, the change in technical efficiency is lower than one, signifying that there was a regression in this respect in the period. The breakdown of the score for the change in technical efficiency into pure technical efficiency change (column 3) and scale-efficiency change (column 4) shows mixed results, with some plants obtaining simultaneous gains in both areas and others obtaining gains in one, but losses in the other. The improvement in pure technical efficiency, which signifies an improvement in managerial

Table 1. 2005 to 2010 total efficiency-window analysis.

	2005	2006	2007	2008	2009	2010		Mean efficiency	Standard division	Total range
Canada	0.683	0.789	0.842				0.771	0.778	0.0446	0.159
Canada		0.732	0.772	0.808			0.771			
Canada			0.767	0.802	0.808		0.792			
Canada				0.802	0.808	0.728	0.779			
$CR_{1,m}$	x	0.057	0.075	0.006	0.000	x	CR_1	0.075		
France	0.766	0.794	0.875				0.812	0.855	0.0417	0.145
France		0.836	0.871	0.912			0.873			
France			0.828	0.880	0.882		0.863			
France				0.880	0.882	0.858	0.873			
$CR_{2,m}$	x	0.042	0.047	0.032	0.000	x	CR_2	0.047		
Germany	0.616	0.659	0.700				0.658	0.678	0.0442	0.132
Germany		0.634	0.662	0.747			0.681			
Germany			0.651	0.733	0.689		0.691			
Germany				0.733	0.689	0.625	0.682			
$CR_{3,m}$	x	0.025	0.048	0.015	0.000	x	CR_3	0.048		
Italy	1.000	0.991	1.000				0.997	0.998	0.0052	0.016
Italy		1.000	1.000	1.000			1.000			
Italy			1.000	1.000	1.000		1.000			
Italy				1.000	1.000	0.984	0.995			
$CR_{4,m}$	x	0.009	0.000	0.000	0.000	x	CR_4	0.009		
Japan	1.000	1.000	1.000				1.000	1.000	0.0000	0.000
Japan		1.000	1.000	1.000			1.000			
Japan			1.000	1.000	1.000		1.000			
Japan				1.000	1.000	1.000	1.000			
$CR_{5,m}$	x	0.000	0.000	0.000	0.000	x	CR_5	0.000		
Netherlands	0.693	0.830	1.000				0.841	0.907	0.1000	0.307
Netherlands		0.794	0.925	1.000			0.906			
Netherlands			0.917	1.000	0.950		0.956			
Netherlands				1.000	0.950	0.825	0.925			
$CR_{6,m}$	x	0.036	0.083	0.000	0.000	x	CR_6	0.083		
Sweden	0.628	0.648	0.764				0.680	0.694	0.0557	0.1484
Sweden		0.616	0.713	0.764			0.697			
Sweden			0.704	0.754	0.672		0.710			
Sweden				0.754	0.672	0.639	0.688			
$CR_{7,m}$	x	0.032	0.061	0.010	0.000	x	CR_7	0.061		
Switzerland	0.594	0.592	0.664				0.616	0.635	0.0383	0.121
Switzerland		0.565	0.625	0.686			0.625			
Switzerland			0.612	0.673	0.655		0.647			
Switzerland				0.673	0.655	0.631	0.653			
$CR_{8,m}$	x	0.027	0.051	0.014	0.000	x	CR_8	0.027		
United Kingdom	0.920	0.913	0.980				0.938	0.908	0.0667	0.221
United Kingdom		0.866	0.915	0.981			0.920			
United Kingdom			0.902	0.975	0.855		0.911			
United Kingdom				0.975	0.855	0.760	0.863			
$CR_{9,m}$	x	0.047	0.078	0.006	0.000	x	CR_9	0.078		
USA	1.000	0.978	1.000				0.993	0.995	0.0119	0.037
USA		0.963	1.000	1.000			0.988			
USA			1.000	1.000	1.000		1.000			
USA				1.000	1.000	1.000	1.000			
$CR_{10,m}$	x	0.014	0.000	0.000	0.000	x	CR_{10}	0.014		

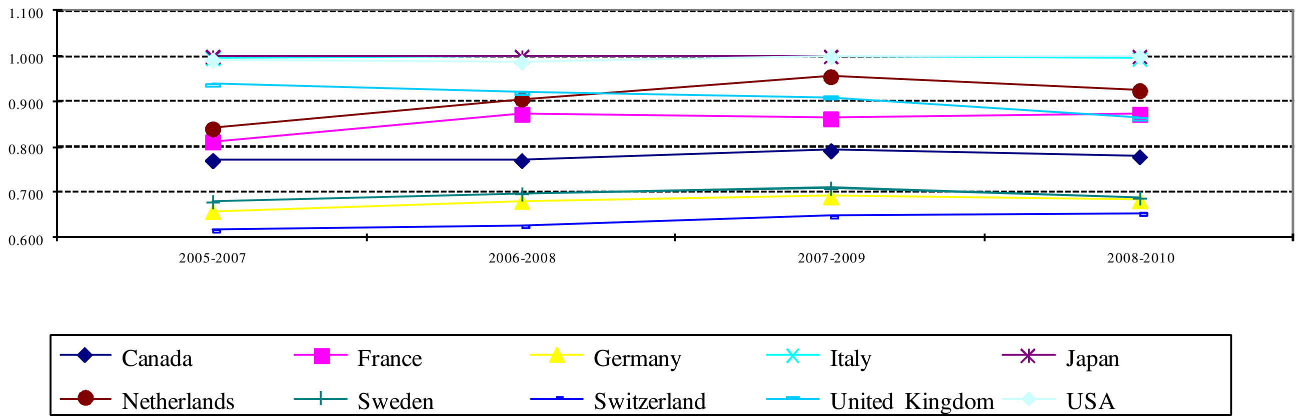

Figure 2. Window analysis result.

Table 2. Malmquist productivity index summary of annual means.

Country	Efficiency change	Technological change	Pure efficient change	Scale-efficient change	Total productivity change score (MPI)
2005-2006	1.012	1.057	1.004	1.008	1.069
2006-2007	1.017	1.033	1.026	0.991	1.050
2007-2008	0.997	1.011	0.955	1.045	1.008
2008-2009	1.011	0.895	1.055	0.958	0.904
2009-2010	1.017	1.022	1.006	1.011	1.039
Mean	1.011	1.002	1.008	1.002	1.013

Table 3. Malmquist productivity index summary of countries means.

Country	Efficiency change	Technological change	Pure efficient change	Scale-efficient change	Total productivity change score (MPI)
Canada	1.000	0.998	1.000	1.000	0.998
France	1.043	0.991	1.042	1.001	1.033
Germany	1.030	0.990	1.039	0.992	1.020
Italy	1.026	1.004	1.000	1.026	1.030
Japan	0.995	0.992	1.000	0.995	0.988
Netherlands	1.017	1.009	1.004	1.013	1.027
Sweden	1.000	1.012	1.000	1.000	1.012
Switzerland	1.000	1.031	1.000	1.000	1.031
United Kingdom	0.995	0.997	1.000	0.995	0.992
USA	1.000	0.996	1.000	1.000	0.996
Mean	1.011	1.002	1.008	1.002	1.013

skills, shows that there was investment in organizational factors associated with the management of plants, such as a better balance between inputs and outputs, best-practice initiatives, more accurate reporting, an improvement in quality, and so on. The scale efficiency, which is the consequence of size, increases in the period for many plants, due to the increase in capacity utilization (Barros, 2008). It is important to note that the mean amount of technical efficiency improvement is 1.011 (mean), the mean value of pure technical efficiency change is 1.008 and the mean value of scale-efficiency change is 1.002.

Technological change (column 2) is the consequence of innovation, that is, the adoption of new technologies, by best-practice hydroelectric plants (Barros, 2008). Its mean value is 1.002, and this index is lower than one for some group of ten. The value of technological change is larger than one for Italy, Netherlands, Sweden and Switzerland. This indicates that innovation improved in the period for Italy, Netherlands, Sweden and Switzerland, meaning that there was investment in new technologies (methodologies, procedures and techniques) and in the commensurate skills upgrades related to this. However, regarding the Canada, France, Germany, Japan, United Kingdom and USA showing a downward movement in terms of technological change, this is a primary area of concern.

Conclusions

The study analyzes the capacity utilization of HRST of group of ten for the period 2005 to 2010. Capacity is defined as the ability of a firm or industry to produce a potential output (Vestergaard et al., 2003). The study has indicated how to use DEA approach to identify individual year that are less efficient to other comparable year in terms of output factors relative to input factors. The most recent style in measuring efficiency is data envelopment analysis, which is a linear program approach based on this concept. Data envelopment analysis measures the efficiency of decision making units by doing linear program for each in comparison to other units. Accordingly the decision making units lie on frontier curve is efficient in choosing the optimal mixture of inputs to achieve the aimed level of outputs. Besides we make use of data envelopment analysis to advise inefficient units by doing certain change in inputs and /or outputs to improve their efficiencies.

This paper applies DEA windows analysis in order to determine the efficiency of capacity utilization of HRST of group of ten over time. This approach is advocated in favor of the commonly used cross-sectional data analysis. We have shown how this approach enables the calculation of efficiency scores even for a small number of different units and a fairly large number of variables. We can use DEA Window Analysis to evaluate the efficiency of different countries under a long term and obtain a best industry that is relatively more efficient for performance. The issue of how same period efficiencies should be defined in a window analysis was discussed and illustrated empirically. In a situation which industries has made a recent investment to achieve beneficial results in the future, or simply just as a result of random effects, the traditional cross-sectional approach may produce misleading results. Observing the average efficiency values, Japan is the highest with a mean of 1.000. On top of that, Japan has the lowest standard division of 0.000. In a highly variant demand changing environment, Japan has a quite stabilized performance over the years. The second best country is USA. It has relatively high efficiency over the periods, and their variances are not too big either; therefore, the overall performance of the system under USA is quite stabilized too. Regarding the CR value, the best country is Japan, and the second best is Italy. Japan also has the best TR value of 0.000, followed by Italy and USA.

Then, we conduct DEA Malmquist productivity approach to identify the major source of productivity growth and separate the catching effect from efficiency changes over time due to technological advancements. The DEA Malmquist productivity approach shows that in-depth information can be obtained by analyzing each individual component of MPI. Such analyses are sometime very critical in capturing an industry's performance comprehensively. Through an analysis of the components of the MPI, we reveal the managerial implication of each component. The results from these analyses are then further examined using the MPI approach and its decomposition. Hence we saw the separation of the catching up effect from the frontier shift, and we clearly observed how the frontier shift is the determinant for productivity growth, with the catching up being neutral or negative depending on the assumptions used. From the results of MPI, we know that industrial industrialist not only enhance their managerial skills but also increase and improve innovative performance and upgrade technology level.

Canada and New Zealand have super competitiveness. Canada's educational environment is especially strong. Both countries are behind in the investment and productivity factors. Among all global 10, these two countries perform inadequately and there is special need to increase research funding.

Research investment is greatest in Sweden, making that country highly competitive. However, Sweden needs to increase its productivity. Investment and productivity factors suggest fair performances in the UK and France, but both countries lack technical infrastructure, especially in the "scientific interest in youth" factor. As long as that remains underdeveloped, it will stunt the competitiveness of their technological human capital. Italy and Spain have room for improvement in several areas, as their technological human capital competitiveness is quite weak. By focusing on its geographical advantages as critical strategies for development, the Netherlands has expanded its economic abilities and utilized its human resources in the European Union.

It is no surprise that the USA and Japan have a high degree of HRST competitiveness. American policies are geared toward maintaining the country's position of technological leadership. Since the 1980s, a series of laws has intensified research regarding new network systems, and other policies encourage management innovations that support government research organizations and universities, as well as methods of technology transfer and dissemination to the industrial sector. Well-defined intellectual property rights that protect research results encourage industries to cooperate and invest in smaller high-tech companies. Japan's extensive investment into research and human capital drives that country's research efficiency. This in turn generates superb human capital competitiveness. Germany also generates high productivity. The infrastructure criteria for Germany suggest that it will continue strengthening its infrastructure, especially in the educational sector, with comprehensive policies to continue the current pace of growth.

There are two extensions to which this study can be undertaken. Firstly, although the input side of the DEA model considered all relevant input dimensions in our industry, the output side bears re-examination. Our study only considered two industry performance measures (namely, number of patents and annual sales) due to certain limitations in the sample size associated with DEA implementation. Future studies should consider a more extensive set of business performance measures. Of particular interest would be a DEA model incorporating market-oriented measures such as market share and sales growth.

Secondly, in evaluating the relative efficiency scores using DEA, we did not restrict any input or output weights. This may affect the results if certain input or output measures are more important than others. In future research, it may be interesting to identify such weights to reflect relative importance and integrate them into the analysis. This would provide more robust results and conclusions.

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