English in the Teaching of Mathematics and Science Subjects (ETeMS) Policy

Implications for the Performance of Malaysian Secondary Schools in Mathematics and Science Subjects

Ihsan Ismail
Warwick Business School
University of Warwick
Coventry, CV4 7AL
United Kingdom

Telephone	**: + 44 (0)24 7652 4306**
Fax:	**: + 44 (0)24 7652 3719**
Email	**: Ihsan.Ismail06@phd.wbs.ac.uk**

Supervisors : 1. Dr Victor Podinovski
Email: Victor.Podinovski@wbs.ac.uk

2. Dr Estelle Shale
Email: Estelle.Shale@wbs.ac.uk

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Abstract

The introduction of ETeMS policy in Malaysia has raised many debates on the effectiveness of the policy and the ability of the schools, teachers and students to adapt to the new medium of instruction. The intentions in this study are to look at the implications of the policy for the school performance in mathematics and science subjects and to test for any significant different in the performance of schools in different location and type. Data envelopment analysis (DEA) model was developed to measure school performance and Malmquist index was used to measure the change in school performance over time. Non-parametric statistical tests were used to test for significant difference in the performance of schools in different location and type.

1. Introduction

One of the most recent and important education policies in Malaysia is the usage of English language in the teaching of mathematics and science subjects (ETeMS). The Malaysian government has announced the change in the medium of instruction for mathematics, science and technical subjects from Malay language to English following a growing concern over the decrease in the standard of English among Malaysian students. This change in policy was deemed necessary to ensure that Malaysians are able to keep abreast with scientific and technological development that is mostly recorded in the English language. At the same time, this move is envisaged to provide opportunities for students to use the English language and therefore increase their proficiency in the language (Education, 2002).

The intentions in this study are to look at the implications of the policy for the school performance in mathematics and science subjects and to test for any significant different in the performance of schools in different location and type. This type of research is important, as it will provide a clearer picture of how the schools performance in mathematics and science subjects are affected by the policy and whether schools in certain location or type are benefiting from the policy. This study would contribute to a new understanding of the implications of the policy for the schools performance in mathematics and science subjects.

Data envelopment analysis (DEA) with hybrid return to scale (HRS) model was developed to measure school performance in mathematics and science subject. The resulting efficiency scores were used to calculate Malmquist index to find the change in school performance after the implementation of the policy. The Malmquist index was then used with non-parametric statistical tests to check for significant difference in the performance of schools in different location and type.

This paper is structured as follows. The next section gives brief description of DEA. This is followed by a section on Malmquist index. Then, research design is illustrated in section 4. Sampling, data collection procedures and data analysis procedures are described in the following sections. Lastly, summary and conclusion are given briefly in the final section.

2. Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a mathematical method based on the principles of linear programming theory and application. It enables one to assess how efficient an organisation uses the available resources (inputs) to generate a set of outputs relative to other units in the data set (Ramanathan, 2006). DEA was introduced by Charnes *et al.* (1978) to compare the efficiency of organisational units such as local authority departments, schools, hospitals, shops, bank branches and similar cases where there is a relatively homogeneous set of units.

DEA can be used to assess the relative efficiency of a particular organisation or DMU since it is based on multiple inputs and outputs measures, explains productivity without a preceding specification of the functional form relating inputs to outputs, and allows the relative weights of inputs and outputs to vary across DMUs (Mar Molinero and Woracker, 1996, Ganley and Cubbin, 1992, Norman and Stoker, 1991). This is particularly appropriate in the area of education management, given the special characteristics of the production process that takes place in schools (Mancebon and Bandres, 1999). These advantages allow researchers to capture a school's multidimensional performance without the need to specify a single functional form to explain the production process in all schools, or assigning weights to output based on value judgments regarding their relative importance.

There are two main models in DEA i.e. constant return to scale (CRS) and variable return to scale (VRS). CRS models require the assumption of full proportionality between all inputs and outputs. However, such proportionality cannot always be true, although there may be a subset of outputs proportional to a subset of inputs. On the other hand, VRS models assume no proportionality between inputs and outputs. This means VRS is ignoring the fact that some inputs are proportional to some outputs which will lead to the overestimation of the efficiency of units.

To overcome this problem, Podinovski (Podinovski, 2004) has developed a hybrid approach that combines the assumption of CRS with respect to the selected sets of inputs and outputs, while preserving the VRS assumption with respect to the remaining indicators. The resulting hybrid returns to scale model (HRS) exhibit better discrimination than the VRS model. In certain cases, their discrimination surpasses that of the CRS model.

3. Malmquist Index

The Malmquist index, introduced by Caves et al. (1982) reflects progress or regress in efficiency along with progress or regress of the frontier technology over time under the multiple inputs and multiple outputs framework. The enhancement of Mamquist index by Fare et al. (1994) has turned it into the standard approach to productivity measurement over time within the non-parametric literature.

Caves, Christensen and Diewert (1982a and b) define a Malmquist productivity index as:

(1) $$M^t = \frac{D_O^t\left(x^{t+1}, y^{t+1}\right)}{D_O^t\left(x^t, y^t\right)}$$

i.e. they define their productivity index as the ratio of two output distance functions, which both utilize technology at time t as a reference technology. The numerator is the output distance function at time t + 1 based on period t technology. The denominator is the output distance function at time t based on period t technology.

Instead of using period t's technology as the reference technology, it is possible to construct output distance functions based on period t + 1's technology and consequently we may construct a Malmquist productivity index as:

(2) $$M^{t} = \frac{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^{t}, y^{t}\right)}$$

Fare et al (1994) avoid choosing an arbitrary benchmark technology by specifying their Malmquist productivity change index as the geometric mean of the indexes shown in equations 1 and 2. That is:

(3) $$M_O\left(x^{t+1}, y^{t+1}, x^{t}, y^{t}\right) = \left[\left(\frac{D_O^{t}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t}\left(x^{t}, y^{t}\right)}\right)\left(\frac{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^{t}, y^{t}\right)}\right)\right]^{\frac{1}{2}}$$

Equation 4 can also be written as:

(4) $$M_O\left(x^{t+1}, y^{t+1}, x^{t}, y^{t}\right) = \frac{D_O^{t}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t}\left(x^{t}, y^{t}\right)}\left[\left(\frac{D_O^{t}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\frac{D_O^{t}\left(x^{t}, y^{t}\right)}{D_O^{t+1}\left(x^{t}, y^{t}\right)}\right)\right]^{\frac{1}{2}}$$

Fare et al (1994) give the following interpretation to the two terms on the right hand side of equation 5:

Efficiency change = $\dfrac{D_O^{t}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t}\left(x^{t}, y^{t}\right)}$

Technical change = $\left[\left(\dfrac{D_O^{t}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}\right)\left(\dfrac{D_O^{t}\left(x^{t}, y^{t}\right)}{D_O^{t+1}\left(x^{t}, y^{t}\right)}\right)\right]^{\frac{1}{2}}$

Hence, the Malmquist productivity index they derive is simply the product of the change in relative efficiency that occurred between periods t and $t + 1$ and the change in technology that occurred between periods t and $t + 1$.

4. Research Design/Conceptual Framework

Based on literatures on the measurement of school performance, we measured the performance of Malaysian school in implementing ETeMS policy by using inputs and outputs on teachers, students' academic results and environmental factors. Figure 1 presents the conceptual framework underlying the DEA models in this research. Inputs consist of the number of teachers, students' prior achievement (the number of good students on entry) and students' SES. Outputs consist of total number of students and students' academic results (the number of good students on exit). Teaching and learning of mathematics and science at school is the process which utilizes inputs and produces outputs. This is the process that contributes to the school performance and being measured in this research. Schools with the efficiency score of 1 are considered as performing up to the expectations while schools with the efficiency scores of less than 1 need to improve to get better results especially a bigger number of good students on exit.

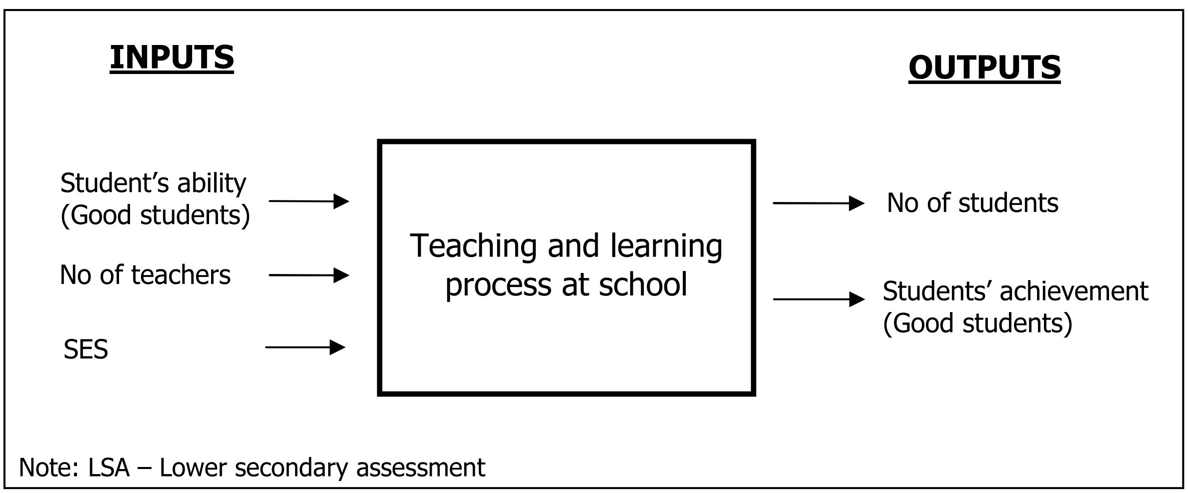

Figure 1: Conceptual framework for DEA model to measure performance in mathematics and science

In this study, the number of teachers is specific to the number of teachers who teach mathematics and science subjects. In Malaysia teachers are normally required to teach more than one subjects. This makes it very difficult to get the number of teachers who teach one specific subjects because there will be redundancy in counting them. To solve this problem, we replaced the number teachers with the number of classes. In Malaysia, the norm used to get the number of teachers is 1.5 teachers for every class. This means we could get the number of teachers who are supposed to teach any particular subjects by looking at the number of classes that take the subject.

We developed HRS output oriented DEA model to measure the overall performance of schools in mathematics and science subjects. This model employs inputs and outputs as shown in Table 1.

INPUTS	OUTPUTS
Math class	Math students
Science class	Science students
Physics class	Physics students
Biology class	Biology students
Chemistry class	Chemistry students
Good math students on entry	Good math students on exit
Good science students on entry	Good science students on exit
Students from high SES	Good physics students on exit
	Good biology students on exit
	Good chemistry students on exit

Table 1: Inputs and outputs in all models

In this table, some of the inputs are proportional to outputs but some are not. The number of classes is proportional to the number of students because classes are formed based on the number of students. Every class should have between 30 to 35 students. Therefore, an increase in the number of students should be followed by an increase in the number of classes proportionately. This means the number of classes and the number of students shows CRS relationship.

On the other hand, the number of good students on entry is not proportional to the number of good students on exit. Although the number of good students on exit will be influenced by the number of good students on entry, other factors in the teaching and learning process also contribute to the students' achievement. Hence, an increase in the number of good students on entry does not necessarily lead to the same increase in the number of good students on exit. As a result, these inputs and outputs show VRS relationship. The number of students from high SES group is also not proportionately related to the number of good students on exit even though more students from high SES are getting good results on exit. This variable is included so that the efficiency score from the models are free from environment factor.

The output oriented HRS model introduced by Podinovski (2004) is as follows:

$$
\begin{aligned}
&\text{Max} \quad z \\
&\text{Subject to} \\
&\sum_{j=1}^{n} \overline{X}_j \lambda_j + \sum_{j=1}^{n} \underline{X}_j \mu_j - \sum_{j=1}^{n} \underline{X}_j \nu_j \leq X_o \\
&\sum_{j=1}^{n} \overline{Y}_j \lambda_j + \sum_{j=1}^{n} \underline{Y}_j \mu_j - \sum_{j=1}^{n} \overline{Y}_j \nu_j \geq Z\, Y_o \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \geq \nu_j \qquad \text{for all } j = 1, \ldots, n \\
&\lambda_j, \mu_j, \nu_j \geq 0 \qquad \text{for all } j = 1, \ldots, n \\
&z \ \textit{free}
\end{aligned}
$$

Based on the above model, the output oriented HRS model in this study is as follows:

$$
\begin{aligned}
&\text{Max} \quad z \\
&\text{Subject to} \\
&\sum_{j=1}^{n} MC_j \lambda_j + \sum_{j=1}^{n} MC_j \mu_j - \sum_{j=1}^{n} MC_j v_j \le MC_o \\
&\sum_{j=1}^{n} SC_j \lambda_j + \sum_{j=1}^{n} SC_j \mu_j - \sum_{j=1}^{n} SC_j v_j \le SC_o \\
&\sum_{j=1}^{n} PC_j \lambda_j + \sum_{j=1}^{n} PC_j \mu_j - \sum_{j=1}^{n} PC_j v_j \le PC_o \\
&\sum_{j=1}^{n} CC_j \lambda_j + \sum_{j=1}^{n} CC_j \mu_j - \sum_{j=1}^{n} CC_j v_j \le CC_o \\
&\sum_{j=1}^{n} BC_j \lambda_j + \sum_{j=1}^{n} BC_j \mu_j - \sum_{j=1}^{n} BC_j v_j \le BC_o \\
&\sum_{j=1}^{n} GMSN_j \lambda_j \le GMSN_o \\
&\sum_{j=1}^{n} GSSN_j \lambda_j \le GSSN_o \\
&\sum_{j=1}^{n} HSES_j \lambda_j \le HSES_o \\
&\sum_{j=1}^{n} MS_j \lambda_j + \sum_{j=1}^{n} MS_j \mu_j - \sum_{j=1}^{n} MS_j v_j \ge ZMS_o \\
&\sum_{j=1}^{n} SS_j \lambda_j + \sum_{j=1}^{n} SS_j \mu_j - \sum_{j=1}^{n} SS_j v_j \ge ZSS_o \\
&\sum_{j=1}^{n} PS_j \lambda_j + \sum_{j=1}^{n} PS_j \mu_j - \sum_{j=1}^{n} PS_j v_j \ge ZPS_o \\
&\sum_{j=1}^{n} CS_j \lambda_j + \sum_{j=1}^{n} CS_j \mu_j - \sum_{j=1}^{n} CS_j v_j \ge ZCS_o \\
&\sum_{j=1}^{n} BS_j \lambda_j + \sum_{j=1}^{n} BS_j \mu_j - \sum_{j=1}^{n} BS_j v_j \ge ZBS_o \\
&\sum_{j=1}^{n} GMSX_j \lambda_j - \sum_{j=1}^{n} GMSX_j v_j \ge ZGMSX_o \\
&\sum_{j=1}^{n} GSSX_j \lambda_j - \sum_{j=1}^{n} GSSX_j v_j \ge ZGSSX_o \\
&\sum_{j=1}^{n} GPSX_j \lambda_j - \sum_{j=1}^{n} GPSX_j v_j \ge ZGPSX_o \\
&\sum_{j=1}^{n} GCSX_j \lambda_j - \sum_{j=1}^{n} GCSX_j v_j \ge ZGCSX_o \\
&\sum_{j=1}^{n} GBSX_j \lambda_j - \sum_{j=1}^{n} GBSX_j v_j \ge ZGBSX_o \\
&\sum_{j=1}^{n} \lambda_j = 1 \\
&\lambda_j \ge v_j \qquad \text{for all } j = 1, \ldots, n \\
&\lambda_j, \mu_j, v_j \ge 0 \qquad \text{for all } j = 1, \ldots, n \\
&z \ free
\end{aligned}
$$

Notation in the models is as follows:

MC	-	mathematics class
SC	-	science class
PC	-	physics class
CC	-	chemistry class
BC	-	biology class
GMSN	-	good mathematics students on entry
GSSN	-	good science students on entry
HSES	-	high socio economic status
MS	-	mathematics students
SS	-	science students
PS	-	physics students
CS	-	chemistry students
BS	-	biology students
GMSX	-	good mathematics students on exit
GSSX	-	good science students on exit
GPSX	-	good physics students on exit
GCSX	-	good chemistry students on exit
GBSX	-	good biology students on exit

5. Population and sample

The population for this study consisted of 281 secondary schools in three northern states of Malaysia namely Kedah, Penang and Perlis. Purposive sampling was used to identify schools within the population that met specific criteria. The criteria for selection included

- Schools that have students taking SPM examination from 2005 - 2008
- Schools that have students taking PMR examination since 2003 - 2006

The rationale for selecting the first criterion was to get enough information on students' achievement after the process of teaching and learning. Since the first batch of students who learned mathematics and science subjects in English took the SPM examination in

2007 and the latest results that we can get are 2008 SPM examination, we only have two years data after the implementation of the policy. To make a fair comparison with performance before the implementation of the policy, we also took the results of SPM examination two years before the implementation of the policy. This is the reason why we came up with the first criterion.

The second criterion is related to the first one in terms of the number of years before and after the implementation of the policy. PMR examination results were used to find the number of good students on entry. Students, who took SPM in 2005 to 2008, took their PMR in 2003 to 2006 respectively. The performance of schools without these data cannot be calculated and have to be omitted from the sample.

Out of 285 upper secondary schools in the three states in 2008, only 227 schools have fulfilled the two specified criteria. These schools were selected as samples for this study. Out of 227 schools, 134 are from Kedah, 71 from Penang and 22 from Perlis. By school-type, 212 are National, 5 Boarding and 10 Religious. Location-wise, 100 are urban schools and 112 are rural schools.

6. Data Collection Procedures

Data on examination results for the selected schools were taken from Malaysian Examination Syndicate (MES). MES is a division under Malaysian Ministry of Education in charged of handling national examination in Malaysia. Two main examinations where the results were used in this study are Lower Secondary Assessment (PMR) and Malaysia Certificate of Examination (SPM). SPM is a major national examination at the end of year 11 and is equivalent to GCSE in England. PMR is a national examination at the end of year 9. PMR is used to determine the stream of the students in year 10 and 11.

Data on the number of students and teachers were taken from an application known as Education Management Information System (EMIS). EMIS is an official application under Malaysian Ministry of Education to collect all information regarding schools, teachers and pupils in all government schools. EMIS is administered by EPRD. Data in EMIS are updated thrice a year that is on 31 January, 30 June and 31 October. However, only data on 30 June is published in the ministry's official statistical book. In this study, data on the number of mathematics and science students as well as the number of mathematics and science teachers were as of 30 June of each year.

7. Data Analysis Procedures

7.1 Programming

Since there is no available DEA software to run the HRS model, LINGO was used to program and solve the mathematical programming of the models. LINGO is a comprehensive tool designed to make building and solving linear, nonlinear and integer optimization models faster, easier and more efficient. LINGO provides a completely integrated package that includes a powerful language for expressing optimization models, a full featured environment for building and editing problems, and a set of fast built-in solvers.

7.2 Statistical Tests

The efficiency scores of each school were used to calculate the Malmquist index to find the productivity change over time (before and after the implementation of ETeMS policy). Malmquist index of each school was then used to compare the performance of schools before and after the implementation of the policy, the performance of schools from different locations and types, and to find factors that associated with and contributed to the schools performance.

The performance of schools from different location was tested for significant difference by using Mann-Whitney test. This is non-parametric test for assessing whether two independent samples of observations come from the same distribution. This test is identical to performing an ordinary parametric two-sample *t* test on the data after ranking over the combined samples.

To test for significant difference in the performance of different type of schools, Kruskal-Wallis test was used. The Kruskal-Wallis one-way analysis of variance by ranks is a non-parametric method for testing equality of population medians among groups. It is identical to a one-way analysis of variance with the data replaced by their ranks. It is an extension of the Mann-Whitney U test to 3 or more groups. Since it is a non-parametric method, the Kruskal-Wallis test does not assume a normal population, unlike the analogous one-way analysis of variance. However, the test does assume an identically-shaped and scaled distribution for each group, except for any difference in medians.

8. Summary and Conclusion

This study intended to look at the implications of the policy for the school performance in mathematics and science subjects and to test for any significant different in the performance of schools in different location and type. The technique used to measure schools performance in science and mathematics subjects is hybrid return to scale DEA model while Malmquist index was used to measure the change in schools performance after the implementation of ETeMS policy. Non-parametric statistical tests such as Mann-Whitney test and Kruskal-Wallis test were used to look for significant difference in the performance of schools in different location and different type of school.

The statistical tests showed that school performance has increased significantly after the implementation of ETeMS policy to conduct the process of teaching and learning mathematics and science subjects in English language. The performance of schools in different States and type were also significantly different with Penang as the best performing State and Boarding school as the best performing school-type. However there is no significant different in the performance of school in urban and rural area. The findings are against the common view on ETeMS policy where most people think that the policy is adversely affecting students' performance in science and mathematics subjects. This might be the result of using a different approach and technique to measure the performance i.e. by taking into account multiple inputs and outputs in developing the measurement model and measuring school performance instead of looking at students' examination results alone.

In conclusion, this study has contributed to the usefulness of DEA in measuring organisational performance by developing a suitable model to measure school performance. It has also contributed to the new understanding of the implications of ETeMS policy for the schools performance in mathematics and science subjects. However, this study can be improved further by including all schools in Malaysia and adding more variables in the models such as the number of students with extra class outside the school and teachers' qualification and experience which might contribute to the students' performance in examination.

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APPENDIX

LINGO programming for HRS model

```
SETS:
  SCHOOL: L, M, V, SCORE, EFF;
  FACTOR07;
  DXF(SCHOOL,FACTOR07): FCT7;
ENDSETS

DATA:
  SCHOOL, FCT7, FACTOR07 =
    @OLE( 'C:\AllSchool.XLS');
    @OLE( 'C:\AllSchool.XLS','HRS07')= EFF;
ENDDATA

MAX = Z;

 @FOR(FACTOR07(J)| J #EQ# 1:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) <= FCT7(UNIT,J));

 @FOR(FACTOR07(J)| J #EQ# 2:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) <= FCT7(UNIT,J));

 @FOR(FACTOR07(J)| J #EQ# 3:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) <= FCT7(UNIT,J));

 @FOR(FACTOR07(J)| J #EQ# 4:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) <= FCT7(UNIT,J));

 @FOR(FACTOR07(J)| J #EQ# 5:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) <= FCT7(UNIT,J));

 @FOR(FACTOR07(J)| J #EQ# 6:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I)) <= FCT7(UNIT,J));

 @FOR(FACTOR07(J)| J #EQ# 7:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I)) <= FCT7(UNIT,J));

 @FOR(FACTOR07(J)| J #EQ# 8:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I)) <= FCT7(UNIT,J));

 @FOR(FACTOR07(J)| J #EQ# 9:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) >= FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 10:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) >= FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 11:
```

```
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) >= FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 12:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) >= FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 13:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) + FCT7(I,J) * M(I) - (FCT7(I,J)
* V(I))) >= FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 14:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) - (FCT7(I,J) * V(I))) >=
FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 15:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) - (FCT7(I,J) * V(I))) >=
FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 16:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) - (FCT7(I,J) * V(I))) >=
FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 17:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) - (FCT7(I,J) * V(I))) >=
FCT7(UNIT,J) * Z);

 @FOR(FACTOR07(J)| J #EQ# 18:
      @SUM( SCHOOL( I): FCT7(I,J)* L(I) - (FCT7(I,J) * V(I))) >=
FCT7(UNIT,J) * Z);

 @SUM(SCHOOL(I): L(I)) = 1;
 @FOR(SCHOOL(I): L(I) >= V(I));
 @FOR(SCHOOL(I): L(I) >= 0);
 @FOR(SCHOOL(I): M(I) >= 0);
 @FOR(SCHOOL(I): V(I) >= 0);

CALC:

   @SET( 'TERSEO', 2);
   @SET( 'STAWIN', 0);

  ! Solve the DEA model for every DMU;
   @FOR( SCHOOL( IU):
      UNIT = IU;
      @SOLVE();
       SCORE( IU) = Z;
      EFF(IU) = 1/SCORE(IU)
      );
ENDCALC
```